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The Department of Defense expends billions of dollars on software development and maintenance annually. Many Department of Defense projects fail to be completed, at large monetary cost to the government, due to the inability of current software cost-estimation techniques to estimate, at an early project stage, the level of effort required for a project to be completed. One reason is that current software cost-estimation models tend to perform poorly when applied outside of narrowly defined domains.

Machine learning offers an alternative approach to the current models. In machine learning, the domain specific data and the computer can be coupled to create an engine for knowledge discovery. Using neural networks, genetic algorithms, and genetic programming along with a published software project data set, several cost estimation models were developed. Testing was conducted using a separate data set. All three techniques showed levels of performance that indicate that each of these techniques can provide software project managers with capabilities that can be used to obtain better software cost estimates.

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A Methodology for Software Cost Estimation Using Machine Learning Techniques

by

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Submitted in partial fulfillment
of the requirements for the degree of

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ABSTRACT

The Department of Defense expends billions of dollars on software development and maintenance annually. Many Department of Defense projects fail to be completed, at large monetary cost to the government, due to the inability of current software cost-estimation techniques to estimate, at an early project stage, the level of effort required for a project to be completed. One reason is that current software cost-estimation models tend to perform poorly when applied outside of narrowly-defined domains.

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I. INTRODUCTION

A. BACKGROUND

The use of computers and computing technology within the Department of Defense continues to grow at an accelerating rate. As the use of computers has expanded, so has the need for computer software. While computer hardware has decreased in cost relative to its performance, the cost of software continues to increase. It is estimated that the Department of Defense spends approximately thirty billion dollars annually in the acquisition and maintenance of software (Boehm, 1987, pg. 43). Virtually no area within the military has escaped the "software invasion." From the million-plus lines of code for the Seawolf submarine's BSY-2 computer system to the two million lines of code in the Navy's NALCOMIS Phase II logistics system, software is now one of the driving factors in the success of the United States military.

Although the technology used to develop software has improved through the use of such methods as object-oriented programming and computer-aided software engineering (CASE), one software management area which remains underdeveloped is software cost estimation. Since the greatest expense in a software development effort is manpower, software cost estimation models focus on estimating the effort required to complete a particular project. This estimate of effort required can then be translated into dollars using the appropriate labor rates. The current cost estimation models available to software project managers fail to provide sound estimates in a consistent manner, even within their

own narrowly defined domains. Improper estimation of costs is a major reason why many Department of Defense software projects have failed. With a decreasing budget for defense, it is of even greater necessity that managers have available to them effective software cost estimation tools.

There are many models available for software cost estimation. One of the more popular models is the Constructive Cost Model, or COCOMO, developed by Barry Boehm while at TRW (Boehm, 1981, pg. 493). This model is based on a database of sixty-three projects developed at TRW during the 1960's and 1970's and is described in detail in Boehm's book, ***Software Engineering Economics***. Part of the reason for the popularity of COCOMO is that it is relatively easy to apply and it resides in the public domain. Other models, such as ESTIMACS, developed by Howard Rubin and currently the property of Computer Associates, Inc., are proprietary due to the nature of the project data from which they were developed. A common thread that exists in all of these models is that they were developed by domain experts and are heavily dependent upon the judgement of the expert for the determination of the model inputs and relationships extracted from the software project data.

An alternative approach to model development that can reduce the need for the domain expert to act solely on judgement is through the use of artificial intelligence (AI), specifically the use of machine learning. While artificial intelligence has been a subject of study since the 1950's, it has periodically been greeted with skepticism for a perceived inability to deliver at the level of performance promised by its proponents. In recent years,

as both computer hardware and software have grown more powerful and the objectives of AI have been better defined, the field of artificial intelligence has seen a resurgence. Techniques are now available that have the ability to provide solid results over a range of problems when appropriately applied. An area of great activity today in artificial intelligence is machine learning. Knowledge acquisition and classification is a very labor intensive task. The computer, with its ability to toil without time off for vacations or holidays, provides a natural platform for the automation of the knowledge acquisition process, or to at least serve as an assistant in the knowledge acquisition process. The application of machine learning to the problem of software cost estimation is the focus of this investigation.

B. OBJECTIVES

Current methodologies for software cost estimation vary widely in their estimates when presented with identical inputs (Kemmerer, 1987, pg. 416). A common characteristic of most cost estimation models is that they tend to provide only marginally useful results within a rigid domain that is often too narrow to be of use when pursuing new types of software development projects. The emphasis of this thesis is to develop a methodology for the application of machine learning techniques to software cost estimation. The three machine learning techniques chosen for this project are neural networks, genetic algorithms, and genetic programming. The performance of the models derived from each machine-learning technique are evaluated and compared with respect to ease of application, accuracy, and extensibility. Additionally, the models are analyzed to

see what insight they can provide into the relative importance of the available input variables.

C. THE RESEARCH QUESTION

The primary research question of this thesis is to determine the feasibility of applying machine learning to the problem of software cost estimation. This research uses the COCOMO data set for model training and the COCOMO and Kemmerer data sets for testing the resulting models. The other important questions of this thesis are to determine the effectiveness of machine-learning techniques when applied to the cost estimation problem and what insight, if any, can be gained from the machine generated models into cost-estimation.

D. SCOPE

The scope of this thesis is to apply the three machine learning techniques to the cost estimation problem using the COCOMO and Kemmerer data sets and to determine the extent to which they are appropriate and insightful to the cost estimation process. The scope of this thesis is not to develop to develop a better model for cost estimation but instead to develop a methodology for the application of machine learning to this problem.

E. METHODOLOGY

This thesis is divided into four steps. First, the sixty-three projects in the COCOMO data set are analyzed and partitioned into training and testing data sets. Secondly, the three machine learning techniques are applied using the training data set as the means for knowledge acquisition. The resulting models are then tested using the COCOMO data not

included in the training set. A variety of parameters and constraints specific to each technique are varied. In a second iteration of this process, all of the 63 COCOMO projects are used as the training set, and a second set of 15 projects, identical to the set used by Kemmerer in his 1987 article in the *Communications of the ACM* is used as the testing set. The goal of this sequence of training and testing is to see how well the various machine generated models can perform across different software development domains. Since the fifteen projects presented by Kemmerer were developed outside of TRW, which is where Boehm's data was obtained, the capability of the models to generalize can be tested.

In the case of neural networks, multiple network configurations are tested. The resulting trained neural networks are ranked on overall performance against actual project effort and against each other.

In the third step of this thesis, a genetic algorithm is applied to the training data using the original COCOMO model structure as a fitness function template in order to obtain a revised COCOMO parameter set. These new values will be used to evaluate the testing data using the Intermediate COCOMO model structure. Initially, the genetic algorithm is relatively unconstrained. In further tests, constraints are added to the genetic algorithm fitness function to determine the effect on the resulting model parameters and on the model's accuracy with respect to the testing data.

Finally, the relatively new concept of genetic programming is applied to the training data set to see what algorithmic models for cost estimation can be derived purely from the

training data with no preconceived functional form or structure provided. The resulting models will again be tested using the test data set.

The resulting models from all techniques will also be analyzed to see what insights, if any, they provide into the overall cost estimation process. The way that the various input variables are used by the machine generated models may provide an opportunity to discover relationships previously unnoticed. This is an additional benefit of using the computer in the knowledge acquisition process and it is explored.

F. ORGANIZATION OF STUDY

Chapter I provides a general background for this study. Chapter II discusses the COCOMO model and the three machine learning techniques in greater detail, including some history and the basic principles of each. Chapter III describes the experimentation process and setup. Chapter IV discusses the results of the various experiments and compares these results with those obtained using the original COCOMO model in its various forms. Additional insights into the cost estimation question will be noted and analyzed at this time. Chapter V is the conclusions and recommendations resulting from this inquiry.

II. MODELS AND MACHINE LEARNING PARADIGMS

A. THE CONSTRUCTIVE COST MODEL

1. Development History

The Constructive Cost Model, commonly referred to as COCOMO, was developed by Barry Boehm in the late 1970's, during his tenure at TRW, and published in 1981 in his text, ***Software Engineering Economics***. This model, which is actually a hierarchy of three models of increasing detail, is based on a study of sixty-three projects developed at TRW from the period of 1964 to 1979. In his text, Boehm describes the development of COCOMO as being the result of a review of then available cost models coupled with a Delphi exercise that resulted in the original model. This model was calibrated using a database of 12 completed projects.

When that model failed to provide a reasonable explanation of project variations when expanded to a 56 project database, the concept of multiple development modes was added. Three development modes were defined as organic, semidetached, and embedded. Organic mode refers to relatively small (< 50 KDSI) stand-alone projects with non-rigorous specifications that typically use small development teams and involve low risk. Organic mode projects are usually thought to have higher levels of productivity than the other two modes due to their small size and flexibility in specifications. Semidetached mode refers to projects of small to medium size (up to 300 KDSI) that involve characteristics of both organic and embedded projects, such as a system that has some

rigorous specifications and some non-rigorous specifications. Embedded mode refers to projects of all sizes that typically have rigorous, non-negotiable specifications that are tightly coupled to either hardware, regulations, operational procedures, or a combination of these factors. Embedded mode projects generally require innovative architectures and algorithms and entail greater risk than organic or semidetached projects of similar size. (Boehm, 1981, pp. 76-77)

Once the three development modes were defined, they were calibrated using the original 56 project database to provide greater accuracy. Seven more projects were later added to the project database for a total of sixty-three. Appendix A contains the entire database. Boehm describes COCOMO as not being heavily dependent on statistical analysis for calibration due to the inherently complex nature of software development. Instead, COCOMO relies on empirically derived relationships among the various cost drivers. These cost drivers are related to attributes associated with the product being developed, the target computer platform, the development personnel, and the development environment. (Boehm, 1981, pg. 493)

The COCOMO model is popular since it is easy for managers to apply and it is widely taught in software management courses. In his text, Boehm provides clear definitions of the model inputs through a variety of tables and charts. This type of presentation allows managers to understand what costs the model is estimating and how the estimates are reached. Therefore, the model can also be used by managers to perform

sensitivity analyses to examine tradeoffs on a variety of different software development issues. (Boehm, 1984, pg 13)

2. Basic COCOMO

Basic COCOMO is the simplest version of the model. It is designed to provide a macro level scaling of project effort based on the mode of development and the projected size of the project in thousands of delivered source instructions (KDSI). Boehm describes its accuracy as limited though, due to the lack of factors to account for differences in project attributes, such as hardware constraints and personnel experience. (Boehm, 1981, pg. 58) The three equations for Basic COCOMO are:

Table 2-1 Basic COCOMO Effort Equations

Mode	Effort
Organic	$MM=2.4(KDSI)^{1.05}$
Semidetached	$MM=3.0(KDSI)^{1.12}$
Embedded	$MM=3.6(KDSI)^{1.20}$

The accuracy of Basic COCOMO is only satisfactory. For the sixty-three projects in the database, Basic COCOMO estimates are within a factor of 1.3 of the actuals just 29% of the time and within a factor of 2 of the actuals just 60% of the time. (Boehm, 1981, pg. 84)

3. Intermediate COCOMO

Intermediate COCOMO tries to improve upon the accuracy of Basic COCOMO by introducing the concept of cost drivers, which act as effort multipliers. Fifteen factors have been identified by Boehm as attributes that affect the effort required on a particular

project. These fifteen drivers are grouped in four attribute categories and are shown in Table 2-2.

Table 2-2 Intermediate COCOMO Cost Drivers

Product Attributes	Computer Attributes	Personnel Attributes	Project Attributes
RELY Required Software Reliability	**TIME** Execution Time Constraint	**ACAP** Analyst Capability	**MODP** Modern Programming Practices
DATA Data Base Size	**STOR** Main Storage Constraint	**AEXP** Applications Experience	**TOOL** Use of Software Tools
CPLX Product Complexity	**VIRT** Virtual Machine Volatility	**PCAP** Programmer Capability	**SCED** Required Development Schedule
	TURN Computer Turnaround Time	**VEXP** Virtual Machine Experience	
		LEXP Programming Language Experience	

These fifteen cost drivers are used in conjunction with a set of scaling equations similar to those used in Basic COCOMO. This nominal effort is then modified by using the product sum of the cost drivers (defined as the Effort Adjustment Factor, or EAF) as defined for a particular project to obtain the Intermediate COCOMO estimate. The nominal equations for the Intermediate COCOMO model are shown in Table 2-3:

Table 2-3 Intermediate COCOMO Nominal Effort Equations

Development Mode	Nominal Effort Equation
Organic	$(MM)_{NOM}=3.2(KDSI)^{1.05}$
Semidetached	$(MM)_{NOM}=3.0(KDSI)^{1.12}$
Embedded	$(MM)_{NOM}=2.8(KDSI)^{1.20}$

The cost drivers are subdivided into literal rating categories that run from Very Low to Extra High. The method for determining which rating category each driver falls into for a specific project is outlined by Boehm in his text. (Boehm, 1981, pg. 119) Once the rating category is determined, the numerical value for the cost driver is obtained from a table. This table can be found in Appendix B. The Intermediate COCOMO estimate of project effort is then given by the equation $(MM)_{EST}= (MM)_{NOM}$*(Effort Adjustment Factor). The Intermediate COCOMO model serves as one of the bases of comparison for the various methodologies presented in the thesis. Intermediate COCOMO is chosen for comparison since the project data published in Boehm's text is only presented at this level of detail.

4. Detailed COCOMO

Detailed COCOMO is an additional refinement of the model that allows the effort estimation to be further detailed. This version of the model attempts to improve the estimate by overcoming two limits of the Intermediate model. First, Detailed COCOMO refines the estimate by introducing cost drivers that vary for the various development phases and, second, it allows for the distribution of various cost drivers over three vertical levels: module, subsystem, and system. Due to the nature of the COCOMO database as

presented in Boehm's text, the Detailed version of the model will not be used as the basis of comparison during the evaluation of the various machine learning paradigms. (Boehm, 1981, pp. 344-345)

B. NEURAL NETWORKS

1. History

The neural network paradigm has a colorful history dating back to the 1950's. This paradigm grew out of the efforts of early artificial intelligence (AI) researchers to construct systems that mimicked the actions of neurons in the human brain. In 1958, Frank Rosenblatt published a paper that defined a neural network structure called a perceptron (Eberhart, 1990, pg. 18). This paper outlined the principles that information could be stored in the form of connections and that information stored in this manner could be updated and refined by the addition of new connections. This research laid the foundation for both types of training algorithms, supervised and unsupervised, that are used in neural networks today.

While work continued in the neural network field during the 1960's and 1970's their usefulness was in doubt until the publication of a paper by John Hopfield, from the California Institute of Technology (Eberhart, 1990, pg. 29). Hopfield's work was important because he identified network structures and algorithms that could be defined in a general nature and he was the first to identify that networks could be implemented in electronic circuitry, which interested semiconductor manufacturers. The publication in 1986 of ***Parallel Distributed Processing*** by the Parallel Distributed Processing Research

Group ensured the rebirth of neural networks by describing in great detail a variety of architectures, attributes and transfer functions (Eberhart, 1990, pg. 32). Since then, the variety and application of neural networks have grown immensely. The Defense Advanced Research Projects Agency sponsored a neural network review in 1988 and published a report on the field (Maren, 1990, pg. 20). This publication tended to validate the field as being worthy of research funding and now there are a variety of journals and publications dedicated to this field, as well as an international society (Maren, 1990, pg. 20).

2. Theory

There are a wide variety of neural network models in use today. One of the most common networks, and the one chosen for use in this thesis, is the backpropagation network. In this case, backpropagation refers to the training method used for this network. The network in operation acts in a feed-forward manner. The basic principle of operation is simple. A backpropagation network is typically constructed of an input layer of neurons, an output layer of neurons, and one or more hidden layers of neurons. Bias neurons may also be defined for each hidden layer. Each neuron (or node) is defined by a transfer function. In the case of the backpropagation network, the function usually has a sigmoid or S-shape that ranges asymptotically between zero and one. The reason for choosing the sigmoid is that the function must be continuously differentiable and should be asymptotic for infinitely large positive and negative values of the independent variables. (Maren, 1990, pg. 93) The neurons in each layer are then assigned a weighted connection

to each neuron in the following layer. These connection weights are established randomly upon initialization of training and then recalculated as the network is presented with the training patterns until the error of the output is minimized. The method that adjusts the weights is known as the Generalized Delta Rule which is a method based on derivatives that allows for the connection weights to be adjusted to obtain the least-mean square of the error in the output. (Maren, 1990, pg. 99) Bias neurons, if used, simply provide a constant input signal to the neurons in a particular layer and relieve some of the pressure from the learning process for the connection weights. A simple network diagram is shown in Figure 2-1.

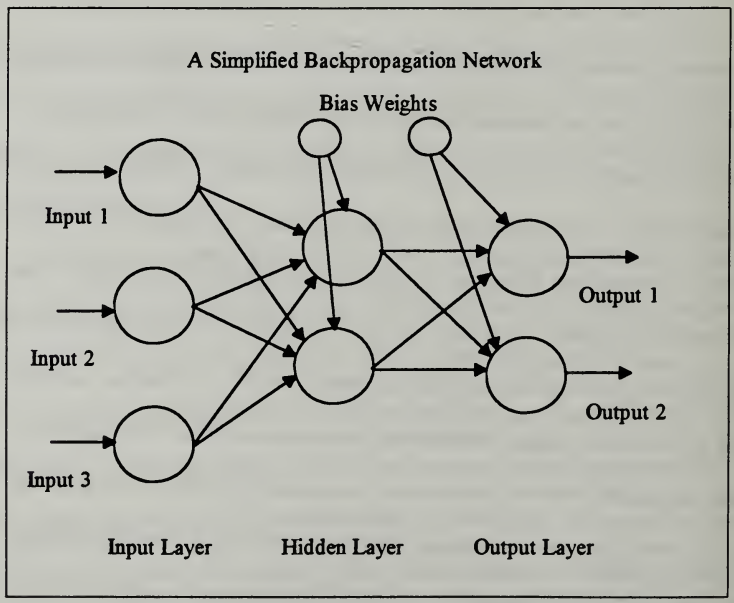


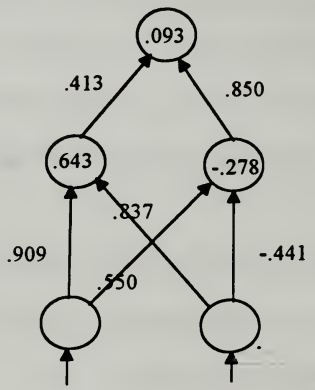
Figure 2-1: A Simple Backpropagation Network

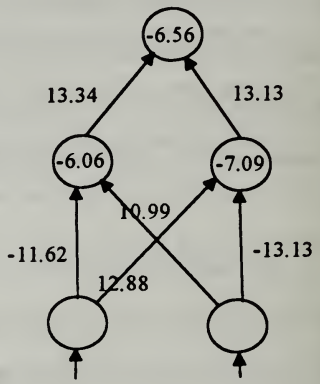
A backpropagation network is capable of generalizing and feature detection because it is trained with different examples whose features become embedded in the weights of the hidden layer nodes (Maren, 1990, pg. 93). An example of the operation of a neural network is provided by Maren and involves a neural network designed to solve an XOR classification problem. The diagram for this network showing the configuration at initialization and upon completion of training is shown in Figure 2-2 (Maren, 1990, pg. 97).

The example given by Maren is a version of the backpropagation network in which each hidden layer neuron can have a threshold value which is added to sum of the inputs to that neuron before the application of the sigmoid transfer function. These threshold values are found using the same Delta rule that is used to find the connection weights. During the training process, the connection weights (and threshold values) are adjusted using the following equation:

$$w_{ij(new)} = w_{ij(old)} + \alpha * Delta(w_{ij,old}) - output_activation_level$$

where w_{ij} stands for the new and old values of the connection weight between node i and node j, and α is a constant that defines the magnitude of the effect of Delta on the weight. Delta describes a function that is proportional to the negative of the derivative of the error with respect to the connection weight and output_activation_level is the output of the jth neuron. This backpropagation of error mechanism allows the weights at all layers to be adjusted as the training process is performed, including any connections between hidden layer neurons. (Maren, 1990, pp. 100-101)





Initialization with Random Weights and Threshold Values

Convergence to Stable Weights and Thresholds After Training Interactions

Initial Results:

Input	Output
(0,0)	0.590
(0,1)	0.589
(1,0)	0.589
(1,1)	0.601

Results After Training

Input	Output
(0,0)	0.057
(0,1)	0.946
(1,0)	0.949
(1,1)	0.052

Figure 2-2 A Neural Network Example of an XOR Problem (Maren, 1990)

An example of the operation of a trained network is seen by examining one of the input combinations in the example provided by Maren (1990) in Figure 2-2. Take the pattern (0,1). This pattern means that a zero is the input to the bottom left neuron of the trained network and a one is the input to the bottom right neuron. Proceeding up to the next layer, a vector multiplication of the inputs and the connection weights is performed to determine the inputs to the hidden layer. In this example the hidden layer inputs are (0*(-11.62))+(1*10.99) = 10.99 for the hidden neuron on the left and (0*12.88) + (1*(-13.13)) = -13.13 for the hidden neuron on the right. The threshold values for these hidden neurons are added to the inputs and then the sigmoid transfer function is applied. For the hidden neuron on the left, this means the input to the transfer function is (10.99+(-6.06)) = 4.94. The activation value of the input 4.94 when applied to a sigmoid transfer function that ranges between zero and one is approximately one. For the hidden neuron on the right, the input to the transfer function is (-13.13+(-7.19)) = -20.32. The activation value when -20.32 is applied to the transfer function is approximately zero. The hidden layer outputs in this example are one for the left hidden neuron and zero for the right hidden neuron. The input to the top, or output, neuron is calculated by taking the product of the hidden layer outputs and the connection weights, or (1*13.34)+(0*13.13) = 13.34. The threshold weight of the output neuron is added to the input from the hidden layer to get the input to the transfer function, which in this case is (13.34+(-6.56)) = 6.78. This number when applied to the transfer function yields a value close to one (0.946), which is the desired answer. (Maren, 1990, pp. 61-62)

3. Applications

Neural networks are currently being used in a variety of applications. Some of the major uses are in the areas of filtering, image and voice recognition, financial analysis, and forecasting (Zahedi, 1991, pg. 27). Commercial neural network software is available from a variety of vendors. Specialized programmable hardware boards that contain chipsets that can mimic the operation of a neural network are also available for very intensive neural network applications. The neural networks in this thesis were developed using a product from California Scientific Software, Inc. called Brainmaker.

C. GENETIC ALGORITHMS

1. History

Nature's capability to find solutions for complex problems through the process of natural selection has fascinated researchers for generations. The ability of organisms to adapt to their environment by altering their characteristics through mating, which provides an opportunity for gene crossover as well as an occasional genetic mutation, has proven to be a powerful technique of problem solving. Genetic algorithms were an outgrowth of early work during the 1950's and 1960's that attempted to combine computer science and evolution with the hope of creating better programs. In the mid 1960's, John Holland developed the first genetic algorithms that could be used to represent the structure of a computer program as well as perform the mating, crossover, and the mutation processes. Since then, genetic algorithms have grown in popularity and have been applied to a wide variety of problems, especially in the field of engineering design, where optimization

involving large numbers of independent variables is a common situation. (Holland, 1992, pg. 66)

2. Theory

Genetic algorithms are in the simplest definition another method for search and optimization. However, they differ from traditional methods such as hill-climbing and random walks in at least four ways (Goldberg, 1989, pg. 7). First, genetic algorithms use codings of the various parameters in a function, not the actual function parameters themselves. This coding usually consists of fixed-length strings of characters that are patterned after chromosomes. Each string, or chromosome, then has a fitness value associated with it which is a measure of how well it performs in terms of the criteria defined for the problem. Second, genetic algorithms perform highly parallel searches using a population of points vice a single point. Third, genetic algorithms use the objective function, or actual payoff information, to determine fitness instead of derivatives or other information. This capability separates the genetic algorithm from those techniques that require gradient information about the function to perform their searches. Instead, the genetic algorithm has the capability to work with the actual function itself. Finally, genetic algorithms use probabilistic rules to make shifts from one generation to the next instead of deterministic rules . (Goldberg, 1989, pp. 7-10)

The easiest way to understand the working of the genetic algorithm is to see it in action. In the following example, similar to the Hamburger Problem presented by Koza (1992, pg. 18), the genetic algorithm is used to maximize a function. The coding of

characteristics in this example is done with the binary digits 1 and 0 and the fitness of each individual is simply the decimal value of the binary representation. The initial population of the first generation, typically referred to as Generation 0 in genetic algorithms, is randomly generated and shown in Table 2-4.

Table 2-4 Generation 0 of the GA

String #	String (X_i)	Fitness $f(X_i)$
1	101	5
2	011	3
3	001	1
4	010	2

As can be seen from Table 2-4, the best individual in the initial population has a fitness of 5, while the worst individual has a fitness of 1. The population average is 2.75. After the initial population is evaluated, the next step in the genetic algorithm is the reproduction and crossover process. The method used to determine which individuals reproduce is normally determined by a method called fitness-proportionate reproduction (Koza, 1992, pg. 21).

In fitness proportionate reproduction, candidates for reproduction are selected for the mating pool by assigning each population member a probability of reproduction based upon each population member's fitness. Under this method, highly fit individuals have higher probabilities for reproduction than lesser fit individuals and the effect of this

reproduction operation is to increase the average fitness of the population. Table 2-5 shows the mating pool for Generation 0 based on fitness-proportionate reproduction.

Table 2-5 Generation 0 Mating Pool Creation

Generation 0			Gen 0 Mating Pool	
String	Fitness	Mating Probability (Fitness/Sum of Fitness)	Mating Pool	Fitness
101	5	5/11=0.454	101	5
011	3	3/11=0.273	101	5
001	1	1/11=0.090	011	3
010	2	2/11=0.182	010	2
Total	11		Total	15
Best	5		Best	5
Average	2.75		Average	3.75

Table 2-5 shows that the average fitness of the population has been increased but that the best-of-generation-individual fitness remains the same. The second genetic process, crossover, is what allows new individuals to be formed which may have better fitness. When the reproduction operation is complete, the crossover operation is performed by selecting two individuals using a uniform random distribution from the mating pool. Selection through a random distribution is possible since membership in the mating pool is proportionate to fitness (Koza, 1992, pg. 25). The selected individuals are separated into fragments by breaking them apart at a randomly selected interstitial point. The appropriate fragments from the parents are then recombined to form new individuals that are then tested for fitness. Table 2-6 shows the crossover sequence.

Table 2-6 The Crossover Operation

Parent 1		Parent 2
101		011
Crossover Fragment 1(F1)		Crossover Fragment 2 (F2)
1--		0--
Remainder 1 (R1)		Remainder 2 (R2)
-01		-11
Offspring 1 (F2+R1)		Offspring 2 (F1+R2)
001		111

When the crossover operation is complete, two new individuals have been created and their fitness is evaluated. The mating pool members not selected for crossover are copied into the next generation. The number of individuals in the mating pool that undergo crossover, the crossover rate, is determined in advance by the individual using the genetic algorithm. The mutation operation, if allowed to occur at all, also happens during the reproduction process. In the mutation operation, a single bit is selected for transformation based upon the probability of mutation, also established in advance by the individual using the genetic algorithm. (Goldberg, 1989, pg. 14) The results of the reproduction and crossover operations in the simple example are shown Table 2-7.

Table 2-7 Generation 1 of the Genetic Algorithm

String	Fitness	Method of Production
001	1	Reproduction/Crossover
111	7	Reproduction/Crossover
101	5	Reproduction
010	2	Reproduction
Best Fitness	7	
Average	3.75	

As can be seen from the table, fitness-proportionate reproduction combined with the crossover operation has improved the average fitness of the population and the best-of-generation fitness (in this case reaching the global optimum). This capability to search and optimize using adaptive techniques without the requirement for an external interface to the user is one of the strengths of the genetic algorithm.

The engine that gives the genetic algorithm its power is called implicit parallelism. This implicit parallelism manifests itself in what Holland described as the Fundamental Theorem. (Goldberg, 1989, pg. 19) The Fundamental Theorem is derived from the concept of schemata. A population in a genetic algorithm consists of a set of strings composed of one's and zero's (a binary representation scheme is commonly used). If the population consists of binary strings, a schema can be thought of as a template that describes subsets of strings using the notation set {1, 0, *}. The asterisk symbol signifies a "don't care" or "wild card" value. A string with value {110} is then, as an example, a member of schema {1**} as well as {*1*}, {11*} and {**0}. In fact, a particular string

in a population is a member of $2^{\text{length-of-string}}$ schema. A schema can be thought of as representing certain characteristics of a candidate solution to the fitness function. As populations of strings (or chromosomes) proceed from one generation to the next through the process of reproduction and crossover, individuals with greater fitness rise in number at the expense of lesser fit individuals. Schemata behave in a similar manner. A schema (or characteristic set) grows at a rate proportional to the average fitness of that particular schema over the average fitness of the population. A schema whose average fitness is above that of the population average will be represented in greater numbers in the succeeding generations. A schema whose average fitness is less than the population average will see its numbers diminish. In fact, above average schema will see their numbers increase in an exponential manner in succeeding populations. This effect of simultaneously increasing the fitness of the population and promoting the exponential growth of beneficial schemata (or characteristics) through the reproduction operation, coupled with the crossover operation that creates population diversity through an orderly exchange of characteristics is what gives the genetic algorithm its implicitly parallel nature. (Goldberg, 1989, pp. 29-33)

3. Applications

The use of genetic algorithms has increased greatly in the past few years as people have realized the benefits they bring to certain types of problems that have resisted solution by more traditional methods. In one case genetic algorithms were used to develop control mechanisms for a model of a complex set of gas pipelines that transport

natural gas across a wide area. Having only various compressors and valves with which to control the gas flow, and with a large time lag between any action and reaction, this problem had no standard analytic solution. A genetic algorithm was developed by David Goldberg at the University of Illinois that was capable of "learning" the control procedure. In another case, Lawrence Davis used genetic algorithms to design communications networks that maximized data flow with a minimum number of switches and transmission lines. General Electric is currently using genetic algorithms in the design of new commercial turbofan engine components. Using a genetic algorithm, General Electric engineers were able to reduce the time required to improve the design of an engine turbine from weeks to days. This is notable since there are at least 100 variables involved in a turbine design as well as a large number of constraints. (Holland, 1992, pg. 72-73) Goldberg's text lists additional uses of genetic algorithms ranging from medical imaging to biology to the social sciences (Goldberg, 1989, pg. 126). There are currently several conferences, both national and international, devoted to the discussion of genetic algorithms.

D. GENETIC PROGRAMMING

1. History

Genetic programming is an exciting new field in computing pioneered by John Koza of Stanford University in the late 1980's. Koza, in his text ***Genetic Programming: On the Programming of Computers by Means of Natural Selection***, describes the core concept of his technique as being the search for a computer program of a given fitness

from the space of all possible computer programs using the tools of natural selection. This approach is different from more traditional artificial intelligence techniques in that for any particular problem using traditional techniques, such as neural networks, the goal is usually to discover a specialized structure that provides a certain output given certain inputs. Koza reframes this statement by saying what we truly want to discover is a certain computer program that will produce the desired output from a given set of inputs. Once the problem is reframed as that of finding a highly fit program within the space of all possible programs, the problem is reduced to that of space search. (Koza, 1992, pg.2)

The technique of genetic programming is not the first attempt at using computers to try to generate programs. Researchers since the 1950's have attempted using various methods to generate programs ranging from blind random search to asexual reproduction and mutation. More recently, researchers in the genetic algorithm field have attempted to use genetic algorithms to generate programs by using ever more specialized chromosome representation schemes or by using a special type of genetic algorithm known as a classifier system to generate programs based on if-then rules (Koza, 1992, pp. 64-66). Koza is the first researcher, however, to develop an appropriate representation scheme and methodology for applying natural selection techniques to the problem of program generation.

2. Theory

The concept of a "highly fit" computer program as a solution to a particular problem is disturbing to most people at first. We are accustomed to the idea of a

computer program being either "right" or "wrong" when applied to a particular problem. Koza counters this sentiment and other similar sentiments by saying that the process of natural selection is neither "right" nor "wrong" but that nature supports many different approaches to the same problem, all of which have a certain "fitness". The key to nature's approach, according to Koza, is that form follows fitness (Koza, 1992, pp.1-7). The requisite tools used in Koza's approach are a well-defined function representation scheme, a method for generating an initial random population of programs, a fitness measurement technique, and a procedure for applying genetic operations to the members of the population.

The representation scheme chosen by Koza for genetic programming is based on a type of structure known as a symbolic expression, or S-expression. Since this type of structure is a key component of the programming language LISP, this language was chosen as the platform for developing genetic programming. It is not a requirement to use this language for genetic programming, but it has many features that facilitated the development of this technique. (Koza, 1992, pp. 70-71) An example of a LISP S-expression is shown in Figure 2-3.

As can be seen from Figure 2-3, a LISP S-expression is equivalent to the parse tree for a particular program, which in this case is 1*(2+3). The ability of LISP structures to serve as both data (to be manipulated) and programs (to be executed) is another of the reasons LISP was chosen as the language for the development of genetic programming. (Koza, 1992, pg. 71)

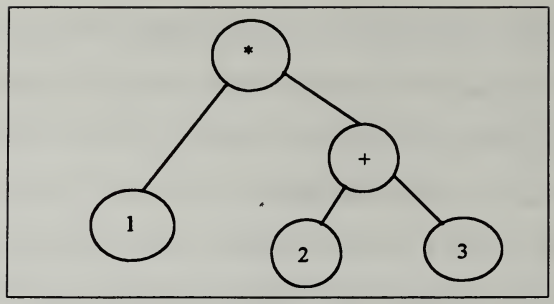


Figure 2-3 A LISP S-expression

In genetic programming, these LISP S-expressions are composed of structures that are derived from a predefined function set and terminal set. The function set consists of whatever domain-specific functions the user feels are sufficient to solve the problem and the terminal set is the arguments that the functions are allowed to take on (Koza, 1992, pg. 80). For instance, the function set may be comprised of mathematical, arithmetic, or boolean operators while the terminal set is usually comprised of variables from the problem domain and an unspecified integer or floating-point random constant. Since it is impossible to determine in advance what the structures will look like, it is necessary to ensure in advance that each function possesses the property of closure (Koza, 1992, pg. 81). The closure property requires that the allowable arguments for any function be well-defined in advance to prevent the function from taking illegal arguments. While this may seem like an imposing task, it is usually not a serious problem and is easily rectified by prior planning of the function definitions. As an example, division by zero is undefined. If the division operator is a member of the function set, then by defining a

special division operator in advance that handles this special case, it is possible to ensure closure on this function. (Koza, 1992, pg. 82)

Once the representation scheme is defined, the initial program structures can be generated (Koza, 1992, pg 91). In Koza's method, the initial structures are generated randomly using a combination of two techniques, "full" and "grow". The root, or beginning, of one of the LISP S-expressions, or trees, is always a function, since a root that consisted of a terminal would not be capable taking any arguments. Once the root function is selected, a number of lines, equivalent to the number of arguments the function requires, are created which radiate away from the function. The endpoints of these lines are then filled by a selection from the combined set of functions and terminals. If another function is selected as an endpoint, the selection process continues onward until the endpoints consist of terminals. There is a preset maximum depth that trees may attain. The terms "full" and "grow" as mentioned above refer to the depth of the trees. In the "full" method, all trees filled until they are at the specified maximum depth. In the "grow" method, the trees are of variable depth. In practice, Koza recommends an approach called "ramped half-and-half" that combines these two approaches (Koza, 1992, pp. 91-92). Koza additionally recommends that each structure generated for the initial random population be checked for uniqueness to ensure a range of diversity of genetic material (Koza, 1992, pg. 93). Figure 2-4 gives a graphical representation of the creation of an individual in the initial population.

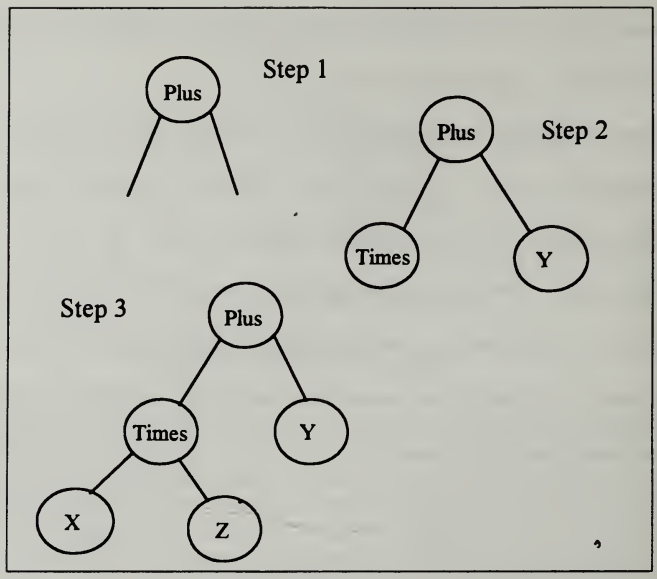


Figure 2-4 Graphical Representation of Tree Generation

Once the initial population is generated the fitness of the individuals in the population must be determined. There are a number of different ways to compute fitness, but in general, most of the methods involve measuring the performance of a member of the population in relation to a predetermined set of fitness cases. As a guide, the set of fitness cases must be representative of the entire domain since they will serve as the basis for achieving a generalized result (Koza, 1992, pg. 95).

After the fitness of the initial random population is calculated, the genetic operations of reproduction and crossover are performed. In genetic programming, the reproduction and crossover operations are designed to happen as separate events rather

than as parts of a two-step process as with the genetic algorithm. Reproduction occurs by copying an S-expression from one generation to the next. Candidates for reproduction are selected by using the fitness-proportionate method or a second method known as tournament selection. In tournament selection, a specified number of population members are randomly selected with replacement. The individual with the best fitness is then reproduced in the next generation. The sampling with replacement is what ensures that fitter individuals survive into succeeding generations. (Koza, 1992, pg. 100)

The crossover operation in genetic programming is more complex than that of the genetic algorithm due to the differences in the structure of the population members. The crossover candidates are selected using the same method chosen for reproduction. This ensures that crossover occurs between individuals in a manner proportionate to their fitness. After two individuals have been selected a separate random number is chosen for each individual which corresponds to a point in each structure. It is at these points that the crossover operation takes place by swapping subtrees. (Koza, 1992, pg. 101) Figure 2-4 shows an example of the crossover operation. The previously described property of closure on the function set ensures that any resulting S-expressions will be legitimate program representations. Since the points selected for crossover are most likely to be at different levels in each structure there are a variety of situations that may result. (Koza, 1992, pg. 103) An individual may reproduce with itself and produce two totally new structures. If the crossover point happens to be at the root of on S-expression, that entire S-expression will become a subtree on the other parent. If the root is selected in both

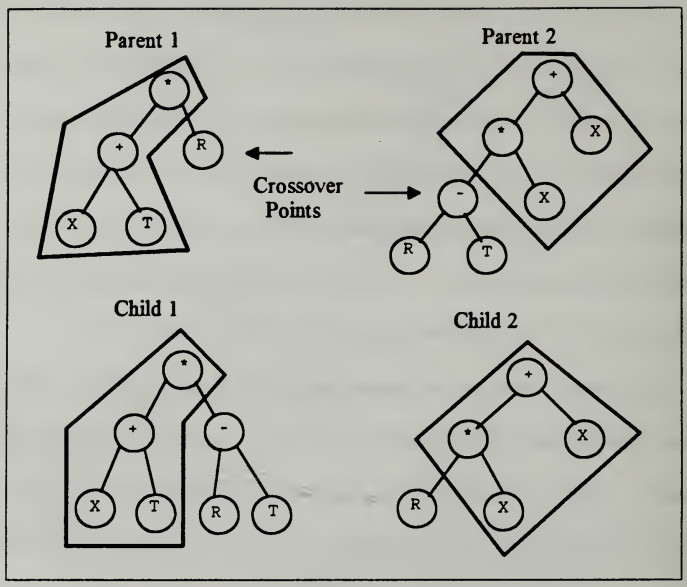


Figure 2-5 The Genetic Programming Crossover Operation

parents, they are both just copied into the next generation. The constraint on maximum structure depth is the only major limit on the crossover operation.

The third genetic operation of mutation is rarely used in genetic programming. The normal argument for its use, in order to promote genetic diversity, is not as important when one considers the variety of structures with different sizes and orientations that are likely to be obtained from the crossover process. Additionally, when the crossover points in both parents correspond to endpoints in each structure, the effect is similar to a mutation at a single point. (Koza, 1992, pg. 106)

3. Applications

Due to its relative youth as a technique, applications using genetic programming are currently confined to mostly experimental problems. Koza does present in his text a copious amount of examples of applying his technique to a wide range of problems, including symbolic regression, game playing strategies, decision tree induction, and artificial life (Koza, 1992, pg. 12-14). In each case, a domain specific function set with the proper closure was determined in advance. Once the function set and the appropriate fitness measure was specified, all of the problems proceeded in the identical manner using a domain-independent implementation of the mechanical operations of evolution. An initial population was generated at random and the genetic operations of reproduction and crossover were used to create succeeding generations. Koza was able to show via empirical methods that genetic programming succeeded in each case to find a solution that satisfied the appropriate fitness measure (Koza, 1992, pg. 4). This ability to solve problems over a wide variety of domains by using a domain-independent method for searching the space of possible computer programs to find an individual computer program is what makes genetic programming an exciting new method of discovery (Koza, 1992. pg. 8).

III. DESIGN OF EXPERIMENTS

A. DATA SELECTION.

The COCOMO data set used for training and testing the machine learning techniques examined in this thesis is drawn from pages 496 and 497 of Boehm's book, ***Software Engineering Economics***. The sixty-three projects used to develop the three versions of COCOMO are summarized in this data base. This data includes the project type, year developed, the development language, the values of the 15 cost drivers, the development mode, and the various COCOMO estimates. The Kemmerer project data was provided by the author in electronic form and is included in Appendix C. The experimental approach taken for each machine-learning technique consisted of a two-step process that required a different training and testing data set for each step. The first step used only the COCOMO data partitioned into training and testing data sets. The second step consisted of using the COCOMO data for training and the Kemmerer data for testing. The partitioning of the COCOMO data set in the first step required two tradeoff considerations.

The first tradeoff involved the size of the training and testing data sets. Machine learning methods perform at their best when they have a large amount of data available for training that is representative of the population, or problem domain. In fact a good guideline is more is always better. However, there are only 63 projects available in the COCOMO data base in the text. In this case, choosing to use too much data for training

reduces the number of data sets available for testing and trivializes the results beyond a certain point. Alternatively, choosing too little data for training reduces the effectiveness of the machine learning techniques. A balance was struck by deciding to break the data into thirds, with two-thirds to be used for training and one-third to be used for testing. This was accomplished by transcribing the data set from the text into a Quattro Pro spreadsheet and then sorting the projects by size and type. Once the data was sorted in this manner, a random number between one and three was assigned to each project. The data was then partitioned into groups based on the random number assigned and each group was analyzed. This cursory analysis showed that for each group the mean project size in thousands of delivered source instructions (KDSI), the average year of development, and the development mode proportions were roughly similar, indicating a reasonable distribution. After this analysis, 42 of the projects were identified as the training set and 21 projects were identified as the testing set. These data sets are included in Appendix D. The same training and testing sets were then used for all of the machine learning techniques examined. The composition of the training and testing data sets for each set of experiments was also kept as identical as possible and consisted of the project size, annual adjustment factor, development mode, and the fifteen COCOMO cost drivers, with limited exceptions.

One effect of partitioning the data in this manner is that the testing data set may not be completely characteristic of the "population". Some testing set projects contained some cost driver values that were not contained in the training data set. This situation

describes the second tradeoff. Hand selecting the data to ensure that every cost driver value represented in the data base was in the training set was initially considered but rejected for two reasons. First, it would probably be meaningless when considering that there are, at a minimum, four values for each cost driver. For fifteen cost drivers this means there are at least 4^{15} possible combinations of cost drivers, and there are only 63 projects in our data set. Secondly, on a more practical basis, several of the cost driver values are only represented once in the project data base, so if they were included in the training data there would be no way of examining the effectiveness of this measure. Therefore, there appeared to be no benefit in ensuring that every cost driver value was fully represented in the training set.

B. NEURAL NETWORK PROCEDURES

1. Neural Network Software

The software used to develop the neural networks in this thesis is BrainMaker Professional v2.5, which is designed and marketed by California Scientific Software, Inc. This software is a DOS-based product manufactured for use on IBM-compatible personal computers. BrainMaker is designed to construct, train, test, and run backpropagation neural networks. It is a menu-driven program that provides the user a large range of control over the design and operation of a neural network. BrainMaker comes with an extensive manual as well as a companion program called NetMaker which can be used to prepare the data files needed by BrainMaker. All of the files used by BrainMaker are in standard ASCII format, so they can be prepared using most any text editor if the user so

desires, although using the NetMaker program speeds up the process since it helps automate the generation of BrainMaker's inputs.

BrainMaker requires two files at a minimum to train. The first file is the network definition file, which tells BrainMaker the key network parameters, such as the number of input and output neurons, the number of hidden layers and hidden neurons, the input and output data definitions and ranges, the learning rate, and the type of transfer function the neurons will use. An example of a network definition file is shown in Figure 3-1. The second file that BrainMaker requires is the fact file. This is the file that contains the data the network will use for training. This file consists of alternating rows of data, with the first row representing one input set and the second row representing one output set. An example of a fact file is contained in Figure 3-2. Additional input files that may be included are a testing fact file and a running fact file. The testing fact file consists of alternating rows of input and output data not included in the training fact file. This data may be used during the training process to judge the prospective performance of the network at user-defined intervals during the training process. When a testing fact file is specified, BrainMaker pauses at the specified interval and tests the current network configuration using the facts in the testing fact file. The results of these tests along with some associated error statistics are written to an output file. The training statistics for each run may also be written to a separate file if this option is activated. The running fact file provides the user with the capability to test the trained network with new sets of inputs in a batch manner and write the results to an output file in a user-specified format.

2. Neural Network Design

The neural network design and training process is very iterative. Since any network configuration will learn some training facts to the user-specified level of tolerance during the training process it is important to have a strategy for determining a broadly effective configuration when beginning the network design process.

```
input number 1 20
output number 1 1
hidden 16 19
filename trainfacts c:\brain\test\cltrain.fct
filename testfacts c:\brain\test\cltrain.tst
learnrate 0.9000 50 0.75 75 0.6000 90 0.5000
learnlayer 1.0000 1.0000 1.0000
traintol 0.1000 0.04 0.8000 100
testtol 0.2000
random 5.0
maxruns 500
testruns 1
function hidden1 sigmoid 0.0000 1.0000 0.0000 1.00000
function hidden2 sigmoid 0.0000 1.0000 0.0000 1.00000
function output sigmoid 0.0000 1.0000 0.0000 1.00000
dictionary input LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
ACAP
AEXP PCAP VEXP LEXP MODP TOOL SCED E ORG SD
dictionary output LOG_MMAC
scale input minimum
0.47712 0.43000 0.75000 0.94000 0.70000 1.00000 1.00000 0.87000 0.87000
0.71000 0.82000 0.70000 0.90000 0.95000 0.82000 0.83000 1.00000 0.00000
0.00000 0.00000
scale input maximum
2.66651 1.00000 1.40000 1.16000 1.30000 1.66000 1.56000 1.30000 1.15000
1.19000 1.29000 1.42000 1.21000 1.14000 1.24000 1.24000 1.23000 1.00000
1.00000 1.00000
scale output minimum
0.77815
```

Figure 3-1: A sample network definition file

There is no way to know which network configuration will be the most successful in learning the data prior to the training process. At best, some authors

recommend general guidelines for network design that can serve as a starting point. The makers of BrainMaker suggest first that there is no little reason to have a network with more than two hidden layers (BrainMaker, 1992, pg. 14-4). They state in their manual that they have never observed a network with more than two hidden layers that could not also be trained on just two layers. As for the number of neurons in the hidden layers, there are two suggestions. The makers of BrainMaker (1992) suggest using the sum of the input and output neurons divided by two, while the authors Eberhart and Dobbins (1990) suggest using the square root of the sum of the input and output neurons plus a couple. Both of these guidelines are based on empirical observations, not any underlying principle. In the end, it is necessary to experiment with a variety of networks to determine a successful configuration. This is probably the most time-consuming portion of the design process but BrainMaker has a method for automating this process to a certain extent.

```
facts
------- 1
1.62324   0.96    1.4   1.08    1.3   1.48   1.56   1.15   0.94   0.86
0.82   0.86    0.9     1  0.91   0.91     1 [ E
2.78175
------- 2
1.36172   0.96   1.15   1.08     1   1.06     1     1   0.87     1     1
1     1     1   0.91  1.1   1.23  [ E
2.36172
------- 3
1.79239   0.81    1.4   1.08     1   1.48   1.56   1.15   1.07   0.86   0.82
  0.86    1.1    1.07  1     1     1 [ E
3.02653
------- 4
1.57978     1   1.15   1.16   1.3   1.15   1.06     1   0.87   0.86     1
0.86    1.1     1  0.82   0.91   1.08  [ E
 2.7185
```

Figure 3-2 A Sample BrainMaker Fact File

3. Preparations for Training

A key aspect in preparing to train a network is data preparation. Due to the nature of neural networks and the way that the training tolerance is calculated, it is necessary to pay particular attention to the way the data is presented to the network. First, all input variables should vary over a roughly similar range between the minimum and maximum values. The reason for this is fairly straightforward. Since every input is connected to each neuron in the first hidden layer, a single input that varies over a large range can tend to "drown out" the other inputs, diminishing their contribution. Secondly, since the inputs and outputs to the network are all normalized, data that varies over a wide range reduces the ability of the network to distinguish small changes. For example, if a significant portion of a particular piece of data ranges between 500 and 600 while a few values range between 10 and 20, the network will have difficulty determining the difference between 10 and 20. As a rule of thumb, smaller changes are better. This becomes particularly important when understanding the concept of network training tolerance.

Tolerance is the statistic used to determine the level of precision to which the network trains. Tolerance is expressed as a percentage of the difference between the minimum and maximum output values. As an example, if the minimum output is 10 and the maximum output is 1000, then a tolerance of 0.1 means that any network output that falls within 0.1*(1000-100) = 90 of the actual output value will be considered correct by the network. Therefore, if the output training values vary over a large range, the accuracy

of the network will be diminished. This required two transformations to the COCOMO data for use with the neural network. Since the KDSI values and the actual man-months vary over a large range, logarithms of these two values were used, which greatly reduced the difference between the minimum and maximum values and increased the ability of the network to learn and predict project effort.

4. Automating the Training Process

BrainMaker has an option which allows the user to specify a range of network hidden layer configurations, as well as other parameters, that can be tested in a variation of a brute force attack (BrainMaker GTO, 1993, pg. 5). This option was used to test three ranges of network configurations that were used in an iterative process to search for the best-performing network configurations. The three ranges tested are summarized in Table 3-1:

Table 3-1 Network Ranges Tested

Number of Hidden Neurons	Number of Layers
1 to 10	1 and 2 hidden layers
10 to 20	1 and 2 hidden layers
15 to 25	1 and 2 hidden layers

The use of this option requires the user to create an additional input file beyond the usual training, testing, and definition files. This setup file contains all the network configuration parameters and the ranges of those that are being varied. In this study, the only parameters varied were the number of neurons and hidden layers, since these two factors have the greatest effect on overall network performance. The remaining network

parameters (which deal mostly with the learning rate associated with the Delta rule) were fixed with the exception of training tolerance, which was allowed to decrease in a stepwise pattern from 0.1 to a limit of 0.04. The stepwise decreases in tolerance are triggered when the network learns all the training facts at the current training tolerance. The testing tolerance was specified as 0.2. An example of the setup file for this option is shown in Figure 3-3:

The training and testing data files consisted of the COCOMO data modified as mentioned previously by changing the KDSI and effort values into logarithmic values. There were 42 training patterns and 21 testing patterns. The network definition file consisted of a generic network definition file that provided the ranges of the input values and the variable names, similar to the file shown in Figure 3-1.

Once the three ranges of configurations had been tested and all of the results written to three output files, the top performing networks were selected. The selections were made by reading all of the output files into Quattro Pro for Windows spreadsheets and sorting the results based on the number of correct outputs for both the training and testing data sets. After the sorting process, the networks shown in Table 3-2 were chosen for further training at a more detailed level. The choice of this iterative process was based upon several factors that mainly involved hardware and software constraints. The hardware constraint concerned the disk space required to save the testing results. In the initial round of testing, the statistics for the testing data set were written to disk every 25 runs. Each of these runs took approximately four to five hours on a 33 MHz 486

```
filenames c:\brain\thesis\cltrain.def c:\brain\thesis\cltrain.fct
c:\brain\thesis\cltrain.tst GTO.STA c:\brain\thesis\test4.ACC
maxruns 400
testruns 25
separate 0.2000
current 111
starttol 0.10000 0.10000 0.00000 0.10000
endtol 0.04000 0.04000 0.00000 0.04000
tolmult 0.80000 0.80000 0.00000 0.80000
tolpct 100 100 0 100
hidden1 1 10 1 10
hidden2 1 10 1 10
hiddenlayers 3 1
decrease 0.10000 0.10000 0.00000 0.10000
addruns 0 0 0 0
inputmin 0.00000 0.00000 0.00000 0.00000
functionmin 0.00000 0.00000 0.00000 0.00000
gain 1.00000 1.00000 0.00000 1.00000
noise 0.00000 0.00000 0.00000 0.00000
blurring 1 0
random 5.00000 5.00000 0.00000 5.00000
delay 1 0
learnrate 1.00000 1.00000 0.00000 1.00000
learninit 0.90000 0.90000 0.00000 0.90000
learnpct1 50 50 0 50
learnrate1 0.75000 0.75000 0.00000 0.75000
learnpct2 75 75 0 75
learnrate2 0.60000 0.60000 0.00000 0.60000
learnpct3 90 90 0 90
learnrate3 0.50000 0.50000 0.00000 0.50000
learnlayer1 1.00000 1.00000 0.00000 1.00000
learnlayer2 1.00000 1.00000 0.00000 1.00000
learnlayerout 1.00000 1.00000 0.00000 1.00000
smoothing 0.90000 0.90000 0.00000 0.90000
smoothlayer1 0.90000 0.90000 0.00000 0.90000
smoothlayer2 0.90000 0.90000 0.00000 0.90000
smoothlayerout 0.90000 0.90000 0.00000 0.90000
```

Figure 3-3 A sample network configuration testing file

Table 3-2 Top Network Configurations

First Hidden Layer Neurons	Second Hidden Layer Neurons
5	8
8	9
10	11
16	19
18	15
24	25

computer and took approximately 300 kilobytes of disk space. Saving the results for every run would have risked filling all the disk space available on the disk and risked crashing the computer while unattended, which would have wasted a training run. Additionally, the resulting data files would have been too large to load into a spreadsheet in order to perform the sorting operations. This is the reason the training was broken into two cycles, with the goal of the first cycle being to identify the networks with the best performance at a macro level. The criteria that was used to determine which networks to choose for further training was based on which networks correctly predicted all 21 projects in the testing data set at some point during their training period. Six network configurations met this criteria. Once these six best network configurations were identified, the second round of training was performed. For this training cycle, network definition files were created for each of the six configurations. All parameters in these definition files were identical except for the number of neurons in the two hidden layers. For these networks, the maximum number of training runs was set to 500. A run is this

sense is defined as a pass through the entire training data set in which fitness statistics are accumulated for the current configuration and weight vector set. The COCOMO training and testing files were provided as inputs. Training and testing statistics for all 500 runs were accumulated in separate files for each of the six configurations. Once this cycle of training was over, the testing and training statistics files were again read into Quattro Pro for Windows spreadsheets and analyzed to determine the optimum number of training runs for each of the six configurations. This optimum point was based on the run where all 42 projects in the training data were correctly predicted and the network training tolerance was at a minimum for the training cycle. When this point was determined for each network, the training process was repeated from the beginning up to this optimum performance point. The analysis of neural network performance is based upon the results obtained from these final versions of the six networks. The definition files for these networks are shown in Appendix E.

This entire network training process starting with the six network configurations was repeated a second time in order to test the performance of the neural network on a data set separate from Boehm's COCOMO data set. In this second round of experimentation, all of the 63 COCOMO projects were used as the training set, and the 15 projects that make up the Kemmerer data set were used as the testing set.

C. GENETIC ALGORITHM PROCEDURES

1. Genetic Algorithm Goal

The goal of the second group of experiments in this thesis was to use a genetic algorithm to determine an optimum set of values for the cost drivers, coefficients, and exponents for the Intermediate COCOMO model. In this group of experiments the inputs to the genetic algorithm included the Intermediate COCOMO model structure,

MM = Effort Adjustment Factor*COEFF*(Adjusted KDSI)EXP**

and the partitioned COCOMO data with two modifications. The first modification to the COCOMO training and testing data set prior to using the genetic algorithm consisted of multiplying the annual adjustment factor and KDSI values together to obtain the adjusted KDSI. This action was taken since the Annual Adjustment Factor provided no additional information to the genetic algorithm process in the absence of information on how it was derived. The second modification consisted of expressing the cost drivers by their literal values, such as HIGH, LOW, or NOMINAL, vice their numeric values.

2. Genetic Algorithm Software

The genetic algorithm software package used was GAucsd 1.4, a C-language genetic algorithm developed by Nicol Schraudolph of the University of California, San Diego, based on previous work by John Grefenstette of the Naval Research Laboratory. The uncompiled C code for GAucsd 1.4 is publicly available via anonymous ftp on the Internet and can be adapted to any machine that has a C compiler. In this case the target

platform was a Sun workstation. The choice of GAucsd 1.4 was based on its availability and ease of use. This package is well-designed in that the user has only to supply a chromosome structure and a fitness function (written in C) that defines the problem. GAucsd 1.4 provides the rest of the functionality required in a genetic algorithm, such as population initialization, crossover, and mutation. GAucsd 1.4 also provides an awk language macro that integrates the user defined fitness function and adds in the code required to implement the genetic algorithm operations. This design feature relieves the user of the task of code integration. (Schraudolph and Greffenstette, 1992, pp. 9-12)

3. GAucsd Preparation

The chromosome structure defined in the genetic algorithm fitness function used in this study consisted of a string of 96 numbers that represented all of the cost driver values, along with the coefficients and exponents for all three project development modes. Since there are a maximum of six values for each cost driver and a total of fifteen cost drivers, the first 90 numbers represented the cost drivers. Although most cost drivers have less than six values, a total of six values were reserved for each driver. This aided in the structure of the problem by allowing the indexing process to operate as if the first 90 numbers represented a pseudo 6 x 15 array. The excess cost driver values in no way impeded the functionality of the genetic algorithm. The numeric values derived by the genetic algorithm were substituted for the literal values in the COCOMO training set which were stored as index values in a C table structure. These first 90 values were allowed by the fitness function to range from 0.5 to 2.0. The 91st through 93rd numbers

represented the coefficients for each development mode and the 94th through 96th numbers represented the exponents for each development mode. These last six values were allowed by the fitness function to range from 0.0 to 4.0. The choice of these ranges was somewhat arbitrary but allowed for a greater range of values than those expressed in Boehm's Intermediate COCOMO model. The actual fitness measure for each member of the population was initially the average relative error of the actual effort in the COCOMO training data set versus the estimated effort calculated by the fitness function. This estimated effort was calculated using the Intermediate COCOMO model as a template. The genetic algorithm derived numeric values for the literal cost driver values, along with the coefficient and exponent values appropriate for each project's development mode then were used as inputs into the Intermediate COCOMO model. The capability to impose constraints on the values generated by the genetic algorithm was also provided and is expanded upon later. The GAucsd user-defined fitness function is shown in Appendix F

4. Initial Genetic Algorithm Benchmarking

Along with the user-defined fitness function, the other input to the GAucsd 1.4 program is the default file that specifies population size, crossover rate, mutation rate, and number of generations. The first step in using the genetic algorithm centered on finding an effective population size and crossover rate to use with the 960 bit chromosome. This was accomplished by a series of test runs using various population sizes and crossover rates while keeping mutation rate and number of generations constant. The test runs are summarized in Table 3-3.

Table 3-3 Genetic Algorithm Benchmark Tests

Population Sizes Tested	100, 200, 1000
Crossover Rates Tested	0.5, 1.5, 2.5, 3.0, 5.0
Mutation Rate	0.00002
Number of Generations	2,000

The training data for this benchmarking process consisted of the entire COCOMO project data set. The entire set was used to examine how well the values derived from the genetic algorithm performed with respect to the values determined by Boehm in his original model. The results of this initial round of benchmarking showed that a population size of 200 and a crossover rate of either 3.0 or 5.0 performed the best in almost every case. The crossover rate greater than one meant that the chromosome underwent several crossovers in each generation. A sample of the genetic algorithm default file is shown in Figure 3-4.

After the optimum population size and crossover rates were determined, nine versions of the fitness function were prepared. These versions differed based on how the fitness of each member of the population was measured and how the previously mentioned constraints were applied. The three fitness measures used in the experiments were average relative error, mean error, and mean-squared error and these measures were calculated as shown in Table 3-4.

```
Experiments = 1
Total Trials = 2000000
Population Size = 200
Structure Length = 960
Crossover Rate = 5.000000
Mutation Rate = 0.00002000
Generation Gap = 1.000000
Scaling Window = -1
Report Interval = 20000
Structures Saved = 20
Max Gens w/o Eval = 0
Dump Interval = 10
Dumps Saved = 1
Options = Aaclu
Random Seed = 3436473682
Maximum Bias = 1.990000
Max Convergence = 0
Conv Threshold = 0.990000
DPE Time Constant = 10
Sigma Scaling = 1.000000
```

Figure 3-4 A Sample Genetic Algorithm Default File

Multiple measures of fitness were tested due to the general nature of adaptive algorithms, of which the genetic algorithm is an excellent example. Different measures of fitness cause different behaviors in the algorithms and affect the learning process. Mean-squared error, for instance, emphasizes large magnitude errors at the expense of

Table 3-4 Genetic Algorithm Fitness Measures

Fitness Measure	Formula
Average Relative Error	$\frac{\Sigma Abs((Estimated - Actual)/Actual)}{\text{Number of fitness cases}}$
Mean Error	$\frac{\Sigma Abs(Estimated - Actual)}{\text{Number of fitness cases}}$
Mean-squared Error	$\frac{\Sigma(Estimated - Actual)^2}{\text{Number of fitness cases}}$

smaller magnitude errors. This type of behavior caused the genetic algorithm to focus on learning the larger software projects that had large errors at the expense of the smaller projects. This behavior led to poor results. Mean error reduced this tendency to a degree, but the best learning performance was found when using average relative error. In these experiments, this fitness measure equalized the effort the genetic algorithm expended learning all of the projects since error was expressed as the average percentage difference between the estimated value and the actual value. A secondary observed benefit of this measure was that both mean error and mean-squared error were also minimized when using this fitness measure even though neither of these fitness measures were explicitly expressed in the fitness function.

5. Genetic Algorithm Constraints

The final aspect of the various fitness functions involved the imposition of various degrees of constraints on the values generated by the genetic algorithm. An inspection of Boehm's COCOMO cost driver, coefficient, and exponent values reveals certain patterns or constraints. For example, in the case of the COCOMO exponents, the magnitude of the exponent increases as the mode shifts from organic to semidetached to embedded. Conversely, the coefficient decreases as the same mode shifts occur. Similar patterns can be seen in the values of the cost drivers. When inspecting the cost driver table, the magnitude of the first seven cost drivers increases when moving from a value of Very Low to a value of Extra High. The opposite movement occurs in drivers eight through fourteen. In this case the magnitude of the driver decreases as the value shifts

from Very Low to Very High. The value of the final cost driver, required development schedule (SCED), moves in a high-low-high manner as the value shifts from Very Low to Very High. These patterns can be interpreted as constraints that the cost driver values should obey. To test whether or not these constraints added to the ability of the genetic algorithm to learn the project data and find an optimal set of values, these constraints were embedded in three versions of the fitness function. In the first version, no constraints were placed on the order of the cost drivers, exponents, or coefficients. In the second version, penalty measures were introduced on the cost drivers so that if the previously identified patterns in the first 14 cost drivers (SCED was allowed to vary without constraint) did not appear in the chromosome, the fitness of the individual was penalized based upon the degree of non-compliance. In the final version of the constrained fitness function, penalty measures were introduced on the generation of the exponents and coefficients as well as the cost drivers.

6. The Genetic Algorithm Testing Process

The nine fitness functions used for training the genetic algorithm were constructed using the three measures of fitness and the three constraint levels previously described. Testing was performed using a population size of 200 and crossover rates of 3.0 and 5.0 with the number of generations set at 5000 for all tests. There were 18 total tests and each test took approximately two to four hours on a Sun workstation. The top twenty chromosomes in each test were saved to an output file and read into a Quattro Pro for Windows spreadsheet. The chromosome values with the best fitness in each run were

translated into their associated COCOMO model values using a previously constructed series of linked spreadsheets. This table of translated COCOMO model values was then linked to the test data set in such a manner as to allow for automatic updating of the test data and its associated performance measures whenever new chromosome data was pasted into the spreadsheet. The results of all 18 tests were processed in the same manner.

A slightly different procedure to that previously described was used when the genetic algorithm was trained using all 63 COCOMO projects and tested with the Kemmerer project data. In this case, the best parameter set from the original genetic algorithm benchmarking tests was used along with the full range of constraints in the fitness function. The use of all of the constraints was based upon the results observed in the first phase of testing. The number of generations was increased from the benchmarking level of 2000 to 5000. The top twenty chromosomes from this run were again saved to an output file that was loaded into a spreadsheet holding the Kemmerer data. The performance of the genetic algorithm with respect to the Kemmerer project set was then calculated.

D. GENETIC PROGRAMMING PROCEDURES

1. Genetic Programming Software

The goal of the final group of experiments in this thesis was to test the ability of genetic programming to derive an explicit cost estimation model given only the COCOMO data and a fitness function. The genetic programming software used was **SGPC: Simple Genetic Programming in C** by Walter Alden Tackett and Aviram Carmi. This software

is based on the original LISP code published by Koza in his book and is available via anonymous ftp from the Santa Fe Institute and the University of Texas. This software provides all the functionality required to apply genetic programming to a variety of problem domains. The genetic operations of population initialization, crossover, reproduction, and mutation are fully supported by this software. The user is only responsible for defining functions specific to the problem at hand, ensuring closure of the functions, and providing the appropriate fitness function and terminal set. This software also has the capability to train and test simultaneously, which reduces the post-experimental processing of the output expressions. Due to the memory requirements and CPU intensive nature of this application, the target platform for this application was a Sun workstation.

2. Genetic Programming Preparation

Preparation for the genetic programming process using the SGPC software involved five steps. In the first step the functions available for use in the S-expressions were defined. Since this set of experiments was basically a problem of regression, the standard mathematical operations of addition, subtraction, multiplication, protected division, and exponentiation were defined as operators in SGPC. The protected division operator is a specially defined division operator that provides closure for the case of division by zero. When this event occurs, the operator is defined to return a value of one.

In the second step the C-language program structure that provides the terminal set (variable declarations) and the training data was constructed. This procedure was

performed using a script written in perl that took the tab-delimited ASCII file containing the COCOMO training data and built a C source code file. This C source code file made the variable declarations that defined the terminal set and created the table structure containing the training data. The training data for this set of experiments consisted of the same projects as those used for the previous experiments. The first round of experiments used the same 42 COCOMO training projects and 21 COCOMO testing projects. In the second round of experiments the entire 63 project COCOMO project set was used for training while the 15 project Kemmerer data set was used as the testing data. The training data input variables were KDSI, the annual adjustment factor, and the fifteen cost drivers. The actual effort associated with each project was the dependent variable. The project mode was not included in the training set since mode is a fixed descriptor of project classification and not a variable. Consideration was given to partitioning the data by mode but this idea was discarded, since the resulting training and testing sets would be so small no conclusions could reasonably be drawn from the results.

The third step in the genetic programming preparation process was the definition of the fitness measure embedded in the "fitness.c" source code file. With the knowledge gained from the sequence of genetic algorithm experiments, the fitness measure for the genetic programming sequence was based on average relative error. The use of average relative error is also supported by the fact that some initial genetic programming test runs performed using the COCOMO data with a different fitness measure, mean-squared error, showed very poor performance.

The fourth step in the process was the preparation of the test data that SGPC used to test the resulting S-expressions during the training process. The test data preparation consisted of using a perl script that took a tab-delimited ASCII file containing the test data and built a C source code file that contained a table of the test data and the associated table declarations.

The fifth and final step of the genetic programming preparation process was to compile the program using a makefile that included the user defined training, testing, and fitness source code files. Once the compilation was complete, the training process was initiated.

The SGPC program required that a number of parameters associated with the genetic programming process be provided by the user in a default file. These parameters include the population size, random seed, reproduction, crossover and mutation parameters, and S-expression size limits. A sample default file is shown in Figure 3-4.

```
seed = 11287
checkpoint_frequency =5
population_size = 2500
max_depth_for_new_trees = 3
max_depth_after_crossover = 10
max_mutant_depth = 4
grow_method = RAMPED
selection_method = TOURNAMENT
tournament_K = 6
crossover_func_pt_fraction = 0.2
crossover_any_pt_fraction = 0.2
fitness_prop_repro_fraction = 0.2
parsimony_factor = 0.01
```

Figure 3-4 A Sample Genetic Programming Default File

A population size of 2500 was used for all the genetic programming experiments in this study. Choice of this population size was basically a compromise between the need to provide a large population to ensure genetic diversity and the memory available on the Sun workstation. It is important to remember that during portions of the genetic programming process, two copies of the entire population are stored in memory. If these populations begin to contain large S-expressions, the memory requirements can be huge, easily exceeding 50 or 60 megabytes. Tournament selection was used to select S-expressions for the reproduction process with a tournament size of six. The parsimony factor included in the default file is an SGPC variable that can be used to reward S-expressions for size of structure as well as performance, with smaller structures being viewed as better than larger ones when performance is equivalent. While the use of parsimony is optional in genetic programming, it was used in the COCOMO runs at various settings. The crossover and S-expression size parameters were also varied so that a total of seven runs using the COCOMO training and testing data and seven runs using the COCOMO and Kemmerer data were completed. The results of each run, which contained the best structure for each generation and its associated fitness, were written to an output file.

Once the testing process was completed the output files were processed by first running an Ami Pro macro on the output file. This macro substituted the Quattro Pro spreadsheet coordinates for each of the input variable names. Using this procedure allowed the best structure from each output file to be pasted directly into a spreadsheet

cell, where the performance calculations were made automatically using a set of linked spreadsheets. This action greatly reduced the processing time required for each output file.

IV. ANALYSIS OF RESULTS

A. MEASURES OF PERFORMANCE

The results of the experiments for all three machine learning techniques were analyzed in the same manner to determine each technique's performance. Three measures of performance were used for all of the techniques. These three measures consisted of the average magnitude of the relative error, the standard deviation of the magnitude of the relative error, and the regression coefficient, R-squared, of the estimated man-months versus the actual man-months. The choice of these three performance measures was based upon the work done by Kemmerer (1987), in which he analyzed the performance of several popular software cost estimation models using a 15 project data set that he developed. These are the same 15 projects that were used as one of the sets of testing data in this study. The use of the magnitude of the relative error is intended to measure the accuracy of each model. The closer this measure is to zero, the greater is the accuracy of the model. The R-squared measure gives the correlation between the estimates of each model and the actual project results. A perfect correlation gives an R-squared value of one. This measure is meant to act as a sort of "reality check" on the models' outputs in seeing whether the project estimates track in a predictable manner with the project actuals.

Since each machine learning experimental procedure involved two phases corresponding to two different software development domains, the measures of performance are able to provide insight in two distinct manners. In the first phase of each

experimental procedure, COCOMO data was used for both training and testing. The performance measures for each of the methods during this phase gives insight into which of the machine generated models perform best when operating in a specified development domain. Where appropriate, comparisons with the estimates provided by Intermediate COCOMO are made. In the second phase of each experimental procedure, the same testing data set Kemmerer (1987) used when he made his study of several popular models was used as the testing data set for the machine generated models. In this phase, it is possible to compare the estimating capabilities of the models developed by the three machine-learning techniques with several well-known cost-estimation models by using the results Kemmerer obtained in his study. These models include SLIM, ESTIMACS, Function Points, and COCOMO. This comparison is useful because it gives an indication of the ability of the machine generated models to generalize across development domains, which is critical for a model, or modeling technique, to be successful.

The machine generated models were also analyzed to see if their structure could provide insight into the general relationships between the input variables and the model outputs. This analysis was performed to see if the machine generated models detected any relationships among the variables that may have gone unnoticed.

B. NEURAL NETWORKS

1. First Phase Results

The initial phase of neural network training involved the use of the COCOMO data set for both training and testing. Six networks were trained using 42 projects from

the COCOMO data set. Testing was conducted using the remaining 21 projects. Table 4-1 shows the performance statistics based on the results of these tests for the six best networks.

Table 4-1 Neural Net Performance Results

COCOMO Training and Testing Data

Network Configuration	Avg Rel Err (%)	Std Dev Err (%)	R-squared (act. vs. est.)
5/8	91.89	90.17	0.755
8/9	89.80	86.26	0.707
11/10	105.96	126.06	0.816
16/19	68.10	68.61	0.726
18/15	136.84	272.68	0.753
24/25	110.17	109.93	0.705
Int COCOMO	16.33	15.76	0.991
XX/XX -- Hidden Layer 1/Hidden Layer 2			
20 Input Neurons -- 1 Output Neuron			

As Table 4-1 indicates, neural networks are not highly accurate in their estimates, but their estimates do correlate relatively good to the actual project efforts. Results of this type are consistent with the typical expectations of a neural network. The strength of neural networks lies in their ability to provide generalized outputs based on their inputs. From this perspective, the neural network results from the first phase of the experiment are positive. The most accurate neural network, with 16 neurons in the first hidden layer and 19 neurons in the second hidden layer, is capable of providing a general

idea of the magnitude of the effort required for a particular project being developed within the same domain in which the network was trained. The correlation coefficient, R-squared, of 0.726 indicates that this estimate has a fairly strong relationship with the actual project effort. Why this particular network performs better than the others is not explicitly determinable. In general, a network is successful when it has just enough neurons to provide a capability for feature detection, but not so many neurons that it just "memorizes" the training data. While not as accurate as the algorithmic model, Intermediate COCOMO, a network has the advantage of requiring less analytical skill to develop and use, and it probably requires less development time. Based on the performance characteristics as observed in Table 4-1, the best use of a neural network would probably be at the early stage of project development, where a manager could perform "what-if" analyses using various input combinations and obtain results very quickly with a minimum of setup. Additionally, by continually retraining the model with new projects the manager could gain further advantages since the network model would be continually calibrating itself through this retraining process. If the organization also uses an algorithmic model for cost estimation, and correlates its estimates with those of the neural network, a sort of "early warning system" that could indicate when recalibration of the algorithmic model is required could be established. A significant drop in the correlation between the two estimation methods could be an indicator that the algorithmic model is in need of calibration.

The most interesting aspect of this phase of experimentation is the effect network configuration has on performance. While the accuracy of the estimate varies over a range of approximately 70 percent, the standard deviation varies over a range of approximately 200 percent. These results indicate that when preparing to use a neural network a good strategy would be to begin with several candidate configurations and continue to maintain and compare them until a statistically sound analysis can be performed to determine the best configuration. As for finding the best configuration, the BrainMaker (1992) thumb rule of using the number of inputs and outputs divided by two or the Eberhart and Dobbins (1990) rule of using the square root of the sum of the inputs and outputs plus a couple would have both provided networks close to the ones found using the brute force search. However, with the power available in current personal computers the BrainMaker brute force search is not an unreasonable or even overly time-consuming approach to take initially.

2. Second Phase Results

In this phase of the neural network experimentation process the entire 63 project COCOMO data set was used for training and the 15 project Kemmerer data set was used for testing. As previously stated, the network configurations from the first phase were retrained to the optimal performance point for the 63 training projects and then tested. The results of this phase of tests are shown in Table 4-2.

The second phase results using the Kemmerer testing are very interesting. As can be seen from Table 4-2, the top performing neural networks are competitive with, and

Table 4-2 Neural Net Performance Results

COCOMO Training and Kemmerer Testing Data

Network Configuration	Avg Rel Err (%)	Std Dev Err (%)	R-squared (Est vs. Act)
5/8	803.24	937.05	0.557
8/9	1,040.57	1,546.72	0.488
11/10	328.84	555.49	0.761
16/19	451.30	683.10	0.742
18/15	621.00	829.12	0.651
24/25	338.12	691.62	0.598
SLIM*	771.87	661.33	0.878
Int COCOMO*	583.82	862.79	0.599
Function Points*	102.74	112.11	0.553
ESTIMACS*†	85.48	70.36	0.134
XX/XX -- Hidden Layer 1/Hidden Layer 2			
* (Kemmerer, 1987, pp. 422-425)			
† ESTIMACS statistics based on 9 of 15 projects			

in some cases superior to, some of the more popular cost-estimation methods in both accuracy and correlation factor. The best network in this phase (11/10), has an accuracy greater than that of either SLIM or Intermediate COCOMO and a correlation factor higher than all of the models except SLIM. While none of the networks could be considered truly accurate, the results of this experiment indicate that networks are worth strong consideration. The best indication that networks deserve attention can be seen by considering the results of the best networks with those of the Intermediate COCOMO.

Both the networks and Intermediate COCOMO are based on the same 63 project data set, yet the best networks perform significantly better. These results seem to indicate that the top networks are capable of capturing some level of meta-knowledge about the relationships between the cost-estimation inputs and the output.

With the relatively small amount of data in both number of inputs and projects that was used for training these networks, the level of performance obtained is still significant. However, the sensitivity to configuration is once again apparent. All six networks "learned" the 63 projects in the COCOMO data set but their performance on the Kemmerer data ranges greatly in both accuracy and correlation. This divergence in the range of performance results appears to to magnified by the change of development domains. This reinforces the suggestion that managers should initially maintain multiple network configurations until some level of confidence is obtained as to which network is truly the top performer.

3. Neural Network Structural Analysis

Although neural networks are relatively easy to construct and operate, it is difficult to explicitly analyze how they are processing their inputs. One method, suggested by a BrainMaker user and posted on Compuserve, can at least provide the user with insight into which inputs affect the behavior of the network the greatest. In this method the first step is to extract the complete set of connection weights from the BrainMaker network definition file and strip the bias weights off of each layer. The second step is to take the absolute value of all the weights. And finally, in the third step, a series of matrix

multiplications are performed, beginning with multiplying the output layer connection weights by the connection weights to the second hidden layer. This process is repeated in a stepwise manner backward through all of the hidden layers until a single weight vector remains. This resulting weight vector shows the magnitude of the connection weights that each input "sees" through the network. Examining this vector can give some indication of which inputs are affecting the network output to the greatest extent. Unfortunately, these results do not indicate whether these weights affect the output positively or negatively since only the magnitudes are used. Still, this approach is useful because the user can at least see what inputs the network considers important. This matrix multiplication analysis was conducted on three of the networks derived in the second phase of the neural network experiments. Two of the top networks, 11/10 and 16/19, along with the worst network, 8/9, were examined using this method. The top 10 connection weight magnitudes for the input neurons in these three networks are shown in Table 4-3.

The results shown in Table 4-3 provide some interesting insights into how each of these networks are manipulating the inputs to the network in order to obtain the effort estimate. For example, the two best networks deemphasize the effect the size of the project has on the effort estimate while the worst network views size as having the top effect on the output. The comparison of how these networks view project size encapsulates the argument made by various researchers that "lines of source code" is in actuality a poor predictor of project effort (Kemmerer, 1987, pg. 418). One factor that all of the networks examined do have in common though is their emphasis on project

Table 4-3 Top Network-Influencing Input Neurons

Network 11/10		Network 16/19		Network 8/9	
Input	Magnitude	Input	Magnitude	Input	Magnitude
TURN	266.28	PCAP	462.70	LOG_KDSI	242.06
CPLX	208.23	TURN	457.40	SD	238.54
AEXP	181.72	STOR	436.58	TURN	205.07
PCAP	168.38	SD	398.55	PCAP	192.67
ORG	166.97	CPLX	388.80	AEXP	179.77
TIME	163.14	LOG_KDSI	371.82	E	175.35
ACAP	159.61	TIME	366.50	ORG	169.01
VIRT	157.12	AEXP	363.64	CPLX	164.78
LOG_KDSI	149.15	ORG	363.12	VIRT	158.68
VEXP	148.42	TOOL	345.72	SCED	141.67

complexity, computer turnaround time, and programmer capability. This emphasis on project complexity and programmer capability is also apparent in the cost driver values that Boehm assigns to these values but the emphasis that the networks place on computer turnaround time is not reflected in the values that Boehm assigns to this driver (Boehm, 1981, pg. 118). Looking at these results from the other direction, the emphasis that Boehm places on the capability of the analyst is not reflected in the analysis of the networks. This driver only appears once in Table 4-3, and is ranked only seventh.

While not conclusive by any measure, this type of analysis can provide a project manager some insight into which network inputs are affecting the output to the greatest

degree and can serve as a type of sensitivity analysis that can provide indications of areas that may possibly require a higher level of attention.

C. GENETIC ALGORITHMS

1. First Phase Results

The first phase of the genetic algorithm experiments used the COCOMO training and testing data sets and Intermediate COCOMO as a model template. In this phase 18 different fitness functions were tested. These fitness functions differed based on the crossover rate, the measure by which the error was determined, and the degree to which the constraints on the values generated by the genetic algorithm were applied. Table 4-4 provides a summary of all of the tests conducted.

As previously mentioned, different fitness measures were tested in order to see which fitness measure most effectively forced the genetic algorithm to find the optimal values of the cost drivers, coefficients, and exponents. The constraints invoked during the various tests reflected the patterns noted in Boehm's values for the cost drivers. The "no constraints" tests meant that all values were free to seek optimal values independent of each other. The "cost drivers only" constraint penalized the fitness of the genetic algorithm proportionate to the degree to which the results failed to match the patterns noted in Boehm's cost driver tables. The "all constraints" constraint extended the "cost drivers only" penalties to the patterns observed in the coefficients and exponents. A graphical representation of the results of all of these experiments is shown in Figure 4-1.

Table 4-4 Genetic Algorithm Test Series Summary

Test Number	Fitness Measure	Constraints	Crossover Rate
1	Avg Rel Error	None	3.0
2	Avg Rel Error	None	5.0
3	Avg Rel Error	Cost Drivers Only	3.0
4	Avg Rel Error	Cost Drivers Only	5.0
5	Avg Rel Error	All Constraints	3.0
6	Avg Rel Error	All Constraints	5.0
7	Mean Error	None	3.0
8	Mean Error	None	5.0
9	Mean Error	Cost Drivers Only	3.0
10	Mean Error	Cost Drivers Only	5.0
11	Mean Error	All Constraints	3.0
12	Mean Error	All Constraints	5.0
13	Mean Squared Err	None	3.0
14	Mean Squared Err	None	5.0
15	Mean Squared Err	Cost Drivers Only	3.0
16	Mean Squared Err	Cost Drivers Only	5.0
17	Mean Squared Err	All Constraints	3.0
18	Mean Squared Err	All Constraints	5.0

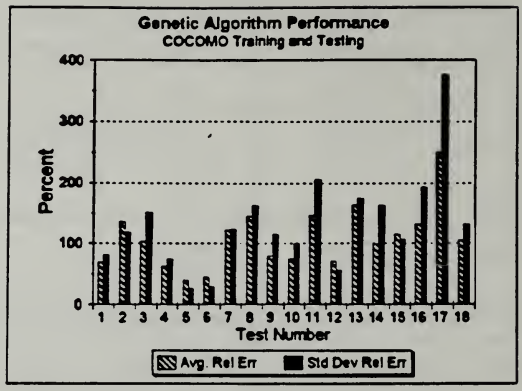


Figure 4-1 Genetic Algorithm Accuracy Performance

Figure 4-1 shows that the best performance in the genetic algorithm experiments was obtained when relative error was used as the fitness measure and the full range of constraints were applied. These performance results indicate that the genetic algorithm is an effective tool for determining an accurate set of numerical equivalents for the literal values in an algorithmic model such as Intermediate COCOMO. The correlation factors for the genetic algorithm derived values are also excellent , and are shown in Figure 4-2.

The ability shown by the genetic algorithm to derive the values for all of the cost drivers, coefficients, and exponents given only a model template, an objective function requirement to minimize the relative error, and some constraints that describe knowledge of the domain is an excellent example of the power that this machine learning technique can provide to the manager.

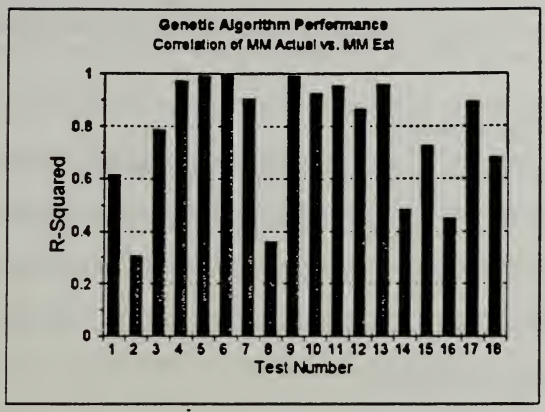


Figure 4-2 Genetic Algorithm Correlation Performance

Boehm (1981, pg. 524) describes situations where it is desirable for COCOMO to be tailored to a particular installation. The procedure outlined for calibrating the model requires solving a system of linear equations. This is time-consuming, tedious work and it also fails to take advantage of any domain knowledge that may have been accumulated by the organization. The genetic algorithm provides an alternative method to this approach that is easier, more extensible, and takes advantage of any domain knowledge that the user wishes to embed in the fitness function. For instance, assuming a COCOMO template, in that the effort required is a function of a particular cost driver set, the project size, and a particular development mode, a user could easily build a new pseudo-COCOMO model

that makes use of any number of cost drivers and modes that the user specifies in the fitness function and chromosome structure. Additionally, the user has the opportunity to build into the fitness function any identified domain knowledge about the relationships that are applicable.

2. Second Phase Results

In the second phase of the genetic algorithm experimentation process the entire COCOMO data set was used for training and the Kemmerer data set was used for testing. The fitness function for this phase used the magnitude of the relative error and the full set of constraints, taking advantage of the knowledge gained previously. The results of this experiment are shown in Table 4-4.

Table 4-4 Phase 2 Genetic Algorithm Performance

COCOMO Training and Kemmerer Testing Data			
Model	**Avg. Rel. Error (%)**	**Std. Dev. Error (%)**	**R-squared**
GA Int. COCOMO	831.01	1,363.18	0.472
GA Basic COCOMO	95.34	111.75	0.578
Basic COCOMO*	610.09	684.55	0.680
Int. COCOMO*	583.82	862.79	0.599
SLIM*	771.87	661.33	0.878
Function Points*	102.74	112.11	0.553
ESTIMACS* †	85.48	70.36	0.134
* (Kemmerer, 1987, pp. 422-425			
† ESTIMACS statistics based on 9 of 15 projects			

The performance of the genetic algorithm-derived values for the cost drivers fared poorly when estimating the effort required for the Kemmerer projects. In fact, the correlation coefficient for the Intermediate COCOMO model derived by the genetic algorithm is lower for the Kemmerer data set than the correlation coefficient between the KDSI and the actual project man-months for this data set (0.47 vs. 0.53), indicating that in this case the Intermediate COCOMO model adds little value. The interesting results in this experiment are obtained by using the Basic COCOMO model which includes just the coefficients and exponents and uses no cost driver values. The estimates obtained when using the genetic algorithm derived values for the coefficients and exponents actually give some of the best results of any model. The strongest conclusion that can be made from these results is that the cost driver values derived by the genetic algorithm are highly sensitive to the domain in which the model was trained. These results have both positive and negative impacts. On the positive side, they reinforce the conclusion from the first phase of genetic algorithm experiments that the genetic algorithm is highly effective at learning a specific software development domain. On the negative side, they indicate that any resulting model is likely to be of little benefit if there is a dramatic shift in the underlying factors in the development environment.

3. Genetic Algorithm Structural Analysis

The surprising accuracy of the Basic COCOMO model as derived by the genetic algorithm is the most interesting result of this experiment. A possible conclusion that can be drawn from this result is that the genetic algorithm has observed a different relationship

between the coefficients and exponents of the COCOMO model than that observed by Boehm. Table 4-5 shows the genetic algorithm coefficients and exponent values compared to those developed by Boehm.

Table 4-5 Comparison of Coefficients and Exponents

Genetic Algorithm Values vs. Boehm Values			
	Embedded	Semidetached	Organic
GA Coefficients	0.429	0.552	2.25
GA Exponents	1.27	1.21	0.510
Boehm Coefficients*	2.8	3.0	3.2
Boehm Exponents*	1.20	1.12	1.05
* (Boehm, 1981, pg. 117)			

This comparison between the genetic algorithm derived values and Boehm's values for the coefficients and exponents indicates that the genetic algorithm detects a greater diseconomy of scale (exponent greater than one) for both the embedded and semidetached modes than Boehm does. Also, the genetic algorithm gives a much greater economy of scale (exponent less than one) to the organic mode than Boehm does. The difference in coefficients between the genetic algorithm and Boehm is probably attributable to the difference in size of the typical projects that are developed in each mode. The large difference seen in the embedded and semidetached coefficients between the two versions is more than likely a reflection of the genetic algorithm's detection of a

stronger relationship between the diseconomy of scale in these two modes rather than the relationship between the scaling effect of the coefficients

The cost driver values derived by the genetic algorithm also show some noticeable differences from those derived by Boehm. Table 4-6 shows the cost drivers.

Table 4-6 Cost Driver Values from GA and Boehm* (GA/Boehm)

	VLOW	LOW	NOM	HIGH	VHIGH	EHIGH
RELY	0.53 / 0.75	0.72 / 0.88	0.95 / 1.00	1.01 / 1.15	1.38 / 1.4	
DATA		0.77 / 0.94	0.81 / 1.00	1.06 / 1.08	1.06 / 1.16	
CPLX	0.79 / 0.70	0.80 / 0.85	1.04 / 1.00	1.28 / 1.15	1.39 / 1.30	2.00 / 1.65
TIME			1.06 / 1.00	1.13 / 1.11	1.45 / 1.30	1.97 / 1.66
STOR			1.16 / 1.00	1.50 / 1.06	1.57 / 1.21	2.00 / 1.56
VIRT		0.83 / 0.87	0.87 / 1.00	0.88 / 1.15	1.06 / 1.30	
TURN		0.96 / 0.87	0.99 / 1.00	1.13 / 1.07	1.34 / 1.15	
ACAP	2.00 / 1.46	1.65 / 1.19	1.54 / 1.00	1.15 / 0.86	0.81 / 0.71	
AEXP	1.84 / 1.29	1.19 / 1.13	1.19 / 1.00	0.83 / 0.91	0.83 / 0.82	
PCAP	2.00 / 1.42	1.07 / 1.17	1.07 / 1.00	1.07 / 0.86	0.76 / 0.70	
VEXP	1.72 / 1.21	1.24 / 1.10	1.08 / 1.00	1.08 / 0.9		
LEXP	1.64 / 1.14	1.56 / 1.07	1.32 / 1.00	1.25 / 0.95		
MODP	1.23 / 1.24	0.99 / 1.10	0.98 / 1.00	0.93 / 0.91	0.92 / 0.82	
TOOL	1.97 / 1.24	1.44 / 1.10	1.32 / 1.00	1.06 / 0.91	0.81 / 0.83	
SCED	1.92 / 1.23	1.56 / 1.08	1.54 / 1.00	2.00 / 1.04	1.70 / 1.10	

* (Boehm, 1981, pg. 118)

The cost driver table shows some similarities in the values derived by the genetic algorithm and the results of the analysis performed on the neural networks. For instance, the genetic algorithm values allow complexity, programmer capability, application

experience, and computer turnaround time to exert a greater variation on the effort adjustment factor than Boehm's values. These are also factors that the top neural networks emphasized. This concurrence of emphasis between two very different machine learning paradigms may be an indication that greater attention should be paid by managers to these areas.

D. GENETIC PROGRAMMING

1. First Phase Results

The first phase of the genetic programming experiments used the COCOMO training and testing data sets. Several runs using the genetic programming software were made using various default values of such factors as, the maximum depth for new trees, the maximum depth after crossover, the crossover factors, and parsimony. The parsimony factor was tried at various levels to see what effect it had on both S-expression length and generalization characteristics of the resulting expressions. The population size was 2500 for all runs, and the total number of generations for each run was 50. For each run, the fittest structure from each generation was saved to an outfile file. The fitness measure used in these experiments was the average magnitude of the relative error. The fitness of both the training and testing data sets were computed each generation.

The results of this phase of experiments were very encouraging and followed a distinctive pattern. Initially, the best of generation fitness for both the testing and training data were roughly of the same magnitude. As each run progressed, the average relative error for both the testing and training data tended to decline until a point was reached

where a divergence was noticed. At this point, the average relative error of the training data continued to decline while the average relative error of the testing data would begin to climb, sometimes in a dramatic manner. It was very apparent from this pattern that the capability of genetic programming to provide a generalized expression is reduced as it learns the training data to a greater and greater degree. This behavior is especially noticeable in the second phase of the genetic programming experience when the COCOMO and Kemmerer data are used.

As for performance, in every run genetic programming was able to learn an expression for the estimated effort that was both accurate and well-correlated. A summary of some of the top performers for the first phase is shown in Table 4-7.

Table 4-7 Genetic Programming Results–Phase One

COCOMO Training and Testing Data						
	Test 1	Test 3	Test 4	Test 5	Test 6	Int COCOMO
Avg Rel Err	39.89	41.9	42.37	42.1	45.32	16.33
Std Dev Err	36.5	39.73	41.06	33.44	40.26	15.76
R-Squared	0.909	0.81	0.71	0.95	0.69	0.991

As Table 4-7 indicates, the accuracy and correlation of the genetic programming derived expressions are worthy of strong consideration by any software manager. The only major hindrance to the easy acceptance of genetic programming as a useful technique comes from examining the expressions that the genetic program generates. These expressions can be both intriguing and intimidating to the uninformed user. It is important

to remember when using genetic programming that the genetic program does not have the domain knowledge nor the prejudices of the user. This means that the genetic program is free to use the terminals and functions provided by the user in any way that the genetic program perceives as "fit". As an example, Figure 4-3 shows one of the expressions generated by the genetic program during this phase of the experiments.

```
MM EST = ((((MODP* KDSI) + ((TIME ^ CPLX ) * (KDSI - LEXP ))) ^VIRT)
^ACAP) + (((ACAP*((STOR^CPLX)*RELY)) + (((ACAP*(PCAP* (TIME* (( KDSI
/(((((PCAP*(KDSI ^STOR))+(DATA+((KDSI ^SCED)* SCED))) ^VIRT) *((DATA+ (KDSI
- SCED )) +KDSI)) +ACAP)) +(KDSI ^STOR))))) + ((( KDSI * VEXP )^ TIME)^VEXP)) -
```

Figure 4-3 A Sample Genetic Programming Expression

As can be seen from Figure 4-3, the expressions generated by the genetic program can be complex and somewhat cryptic, but they are also accurate. The expression shown in Figure 4-3 is the expression used to obtain the Test 1 results shown in Table 4-7. As Table 4-7 shows, this expression has an average relative error of approximately 40 percent and an R-squared value of 0.9.

2. Second Phase Results

The second phase of the genetic programming experiments used the COCOMO data for training and the Kemmerer data for testing. The same variations in program parameters such as maximum tree depth, crossover rates, parsimony, etc., were used in this phase as in the first phase. The same pattern in the fitness measures for both the

training and testing data were also observed but in a much more pronounced manner. In fact, the divergence in fitness between the training and the testing data was so pronounced that the maximum number of generations was reduced from 50 to 20 for this phase of experiments. A summary of some of the top runs for this phase of experiments is shown in Table 4-8. The results from Kemmerer's analysis are included for comparison.

Table 4-8 Genetic Programming Performance Results

COCOMO Training and Kemmerer Testing Data

Test	Avg Rel Err (%)	Std Dev Err (%)	R-squared (Est vs. Act)
Test 2	109.52	125.85	0.78
Test 3	130.97	142.35	0.62
Test 4	59.15	69.5	0.93
Test 9(a)	112.01	132.15	0.90
Test 9(b)	144.24	167.9	0.85
SLIM*	771.87	661.33	0.878
Int COCOMO*	583.82	862.79	0.599
Function Points*	102.74	112.11	0.553
ESTIMACS*†	85.48	70.36	0.134
* (Kemmerer, 1987, pp. 422-425)			
† ESTIMACS statistics based on 9 of 15 projects			

As Table 4-8 indicates, genetic programming is very capable of deriving expressions that can provide highly accurate results across development domains. An

example of the type of expression generated by the genetic program during this phase is shown in Figure 4-4.

```
MM EST = (((TOOL + VEXP.) * RELY ) + (((KDSI * ACAP ) ^ VIRT ) ^
(MODP * TIME ))) + (KDSI ^ STOR )
```

Figure 4-4 A Sample Genetic Programming Expression

The expression shown in Figure 4-4 is the expression used to obtain the results in Test 9(a) shown in Table 4-8. The results obtained from this expression are superior to most of the models tested by Kemmerer (1987) with the exception of ESTIMACS. However, one of the expressions generated by the genetic program during this phase is even superior to ESTIMACS. This expression is the top performer from several of the runs, and is the same expression used to obtain the results shown in Test 4 of Table 4-8. The expression is shown in Figure 4-5.

```
MM EST = ( KDSI + (2.336426) ) ^ STOR
```

Figure 4-5 Top Performing Expression from Phase 2

This expression is extremely simple and yet highly accurate, as the results in Table 4-8 indicate, yet is highly unlikely that a human domain expert would conceive of an expression such as this one. This is where genetic programming shows its usefulness. The ability to conceive of relationships among various factors without the prejudice of one's

own knowledge is what allows the genetic program to succeed in its task. The results from this phase of experiments indicate that genetic programming is an extremely usesful technique for generating cost-estimation models and should be considered as a leading candidate for use as a cost-estimation model generator.

The comparison of the a sample of the results of genetic programming with those obtained by Kemmerer in his study shows that genetic programming is capable of generating a model that is superior to any of these popular cost-estimation models. In fact, upon examining the best models from each generation of all of the runs during this phase showed that during the 20 generation cycle for each run, the genetic program rarely generated a program with over 400% error. This means that at almost any time during any run, the genetic program was generating expressions that were superior to both SLIM and Intermediate COCOMO.

3. Genetic Program Structural Analysis

The analysis of the structures generated by the genetic program is a very complex topic and is currently being studied by a variety of researchers worldwide. Although researchers are of different opinions about the significance of the structures that genetic programming produces, there are some basic characteristics that can be observed.

Analyzing the results of a genetic programming run shows that the genetic programming paradigm can be very inventive. As an example, when Koza (1992, pg. 242) first developed his LISP genetic programming software, the capability to generate constant terms was not included. During an early run involving the discovery of

trigonometric identities he observed a peculiar term in the resulting LISP S-expression. This term is shown in Figure 4-5.

```
2 - Sin(Sin(Sin(Sin(Sin(Sin(Sin(1))*Sin(Sin(1)))))))))
```

Figure 4-5 Genetic Programming Derived Constant

This term evaluates to 1.57, which is very close to the value of Pi divided by two, a constant that is needed often in trigonometric problems. The discovery of this type of inventive behavior by the genetic program led Koza to modify the software to allow for the creation of random constants. Koza (1992, pg. 185) also observed a tendency for the genetic program to take useful subtrees and repetitively use them to perform functions that the genetic program found useful.

The structures derived by the genetic program for the second phase in these experiments varied widely in their size and composition, although the use of parsimony and a reduced maximum tree depth tended to yield shorter structures that performed better across project domains. Examples of some of the structures derived by the genetic program for cost-estimation are shown in Figure 4-6.

Examining the structures in Figure 4-6, it is apparent that the genetic program does not find all of the cost drivers useful. While KDSI, MODP, STOR, and TIME appear with some regularity, other drivers such as TURN and SCED are not used at all. This is where genetic programming can be unsettling to a user. While the user can give copious amounts of data to the genetic program, there is no certainty that all of it will be

Test 2 Generation 6

MM EST = ((AAF ^ PCAP) + LEXP) + (((CPLX + ((((1.615063) * KDSI) * ((DATA * TIME) * TOOL)) + ((KDSI ^ TIME) ^ PCAP))) ^ VIRT) - VIRT)

Validation Fitness= 109.51

Test 3 Generation 6

MM EST = KDSI * (AEXP + TIME)

Validation Fitness= 130.77

Test 9 Generation 6

MM EST = (TOOL + ((KDSI ^ (MODP * TIME)) + (KDSI ^ STOR))) * VIRT

Validation Fitness= 144.16

Test 9 Generation 10

MM EST = (((TOOL + VEXP) * RELY) + (((KDSI * ACAP) ^ VIRT) ^ (MODP * TIME))) + (KDSI ^ STOR)

Validation Fitness= 112.01

Figure 4-6 Genetic Programming Derived Structures

used. The user has to be prepared to deal with structures that have no resemblence to relationships that the user believes to exist within the domain. This factor may be a barrier to acceptance for some managers, but if the models derived are statistically significant in both accuracy and correlation they are hard to dismiss.

V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

The major objective of this thesis was to examine the effectiveness of three machine learning techniques as applied to the field of software cost estimation. The driving factor behind the investigation of machine learning in the cost estimation field is that current software cost estimation models are both inaccurate and not very adaptable across development domains. These are critical areas of weakness since the Department of Defense is the largest single software consumer in the world, and it develops software for a wide variety of domains. Therefore, it is necessary that a software cost estimation model be both accurate and easily adaptable in order to be considered successful. The premise of this research was that there probably were relationships among the various software project factors that the current models did not capture and that a machine learning approach, where the models are derived directly from the data, may prove superior in both performance and adaptability.

The three machine learning techniques studied in this thesis have all proven through the experiments conducted to have great usefulness in the area of software cost estimation. Each technique studied also brings to this field certain particular capabilities.

Neural networks showed a strong capability to capture and learn the project data, and make estimates of reasonable accuracy that exhibited a high correlation with the project actuals. When tested with data from outside the domain in which the networks were

developed, the neural networks showed a strong capability to generalize on the data that was presented to them and make estimates that were superior to those of other well-known models. This capability to make estimates across domains is critical when seeking estimates on new projects with different development environments. Given the limited amount of data that was available for testing the networks, they performed surprisingly well. Neural networks also have an advantage in that they are relatively easy to set up and train, and are certainly within the capabilities of most management personnel. They also have the advantage of being self-calibrating, as long as the network is maintained by continually retraining with data from newly completed projects. While not as accurate as some of the algorithmic models, neural networks are certainly worthy of consideration, especially since they have the ability to deal with non-numeric, or symbolic, data. The best use of a neural network within an organization is probably at the earliest stages where estimates that can at least capture the likely magnitude of a project are the most useful.

The genetic algorithm experiments showed that they were highly effective as a tool for model optimization and calibration. Given no more than a fitness function, a table of literal values describing the projects, and a small amount of domain knowledge in the guise of constraints on the fitness function, the genetic algorithm was able to find a complete set of values for the cost drivers, coefficients, and exponents in the Intermediate COCOMO model. The resulting model values were shown to provide estimates that had a high degree of accuracy and correlation for projects developed within the same domain, but

their performance was not as good when applied to projects outside of the domain in which they were trained. Still, the genetic algorithm proved to be effective as a tool for model calibration and it is easy to apply. The user has only to supply a fitness function that includes the fitness measure, the model function and whatever constraints the user feels necessary for the particular domain. The power of evolution handles the search for an optimal solution. Additionally, the genetic algorithm is highly extensible due to the ability of the chromosome structure to be modified to reflect additional characteristics of the domain. The genetic algorithm is likely to be of the greatest use in a situation where an organization feels they have a model for how their development process functions but they need a method for calibrating the model to the data at hand. The genetic algorithm is very capable in this situation.

In the third set of experiments the very new technique of genetic programming was used as a means for model discovery. In this case, the only inputs provided were the fitness measure, the project data, and a set of functions that were allowed to operate on the data. Upon initializing the population with a random set of programs, the process of evolution then generated models of greater and greater fitness as the genetic program evolved through succeeding generations. The models resulting from this technique were both highly accurate and strongly correlated. These results indicate that genetic programming shows great usefulness as an exciting new approach to the cost estimation problem and has probably the broadest range of uses of any of the techniques studied in this thesis.

In all instances, each of the methods examined in this thesis was capable of generating models that were competitive in both accuracy and correlation with other established cost estimation models. In one case, the machine generated model outperformed all of the more well-known and established models. This level of performance exhibited by machine generated models indicates that they should be given serious consideration by those involved in the software development field, as they offer several advantages. First, they directly reflect the data they are trained with, which automatically gives them an advantage over a models that may have been developed outside of the domain in which it is being applied. Second, they are highly extensible, meaning that any additional knowledge that becomes available regarding the software development process can easily be incorporated in these models. This provides an advantage over the more traditional models in that a machine generated model is easily tailored to the data available. These advantages, coupled with the performance levels noted in the experiments conducted in this study indicate that machine learning is an effective and useful technique for the field of software cost estimation.

B. RECOMMENDATIONS FOR FURTHER RESEARCH

There are several areas that are candidates for further research based on this study. First, additional experiments can be conducted to extend the level of knowledge regarding how each of the techniques should be applied to achieve the greatest effectiveness. Secondly, research can be conducted into coupling these machine learning techniques together in order to create a suite of tools that may be able to provide a superior level of

performance. As an example, one could build an expert system front end that could query a user about project characteristics in order to populate a data base. This expert system front end could then be coupled to a neural network that could provide general estimates, or it could be coupled to the genetic program, which could generate candidate models. It may also be possible to have a neural network monitor the results of the models the genetic program develops, and make a selection as to which model is best for a particular situation based on the user's inputs the expert-system front-end. Finally, a similar set of experiments to those conducted in this study could be performed using data from a variety of domains for training. This may prove insightful, since a certain amount of meta-knowledge about the data would have to be apparent in any models developed using these techniques.

APPENDIX A

COCOMO DATA SET (Boehm, 1981, pg. 496)

Project	MM ACTUAL	TOTKDSI	AAF	RELY	DATA	CPLX	TIME	STOR	VIRT	TURN	ACAP	AEXP	PCAP	VEXP	LEXP	MODP	TOOL	SCED	MODE
1	2,040	113	1	0.88	1.16	0.7	1	1.06	1.15	1.07	1.19	1.13	1.17	1.1	1	1.24	1.1	1.04	E
2	1,600	293	0.85	0.88	1.16	0.85	1	1.06	1	1.07	1	0.91	1	0.9	0.95	1.1	1	1	E
3	243	132	1	1	1.16	0.85	1	1	0.87	0.94	0.86	0.82	0.86	0.9	0.95	0.91	0.91	1	SD
4	240	60	0.76	0.75	1.16	0.7	1	1	0.87	1	1.19	0.91	1.42	1	0.95	1.24	1	1.04	ORG
5	33	16	1	0.88	0.94	1	1	1	0.87	1	1	1	0.86	0.9	0.95	1.24	1	1	ORG
6	43	4	1	0.75	1	0.85	1	1.21	1	1	1.46	1	1.42	0.9	0.95	1.24	1.1	1	ORG
7	8	6.9	1	0.75	1	1	1	1	0.87	0.87	1	1	1	0.9	0.95	0.91	0.91	1	ORG
8	1,075	22	1	1.15	0.94	1.3	1.66	1.56	1.3	1	0.71	0.91	1	1.21	1.14	1.1	1.1	1.08	E
9	423	30	1	1.15	0.94	1.3	1.3	1.21	1.15	1	0.86	1	0.86	1.1	1.07	0.91	1	1	E
10	321	29	0.63	1.4	0.94	1.3	1.11	1.56	1	1.07	0.86	0.82	0.86	0.9	1	1	1	1	E
11	218	32	0.63	1.4	0.94	1.3	1.11	1.56	1	1.07	0.86	0.82	0.86	0.9	1	1	1	1	E
12	201	37	1	1.15	0.94	1.3	1.11	1.06	1	1	0.86	0.82	0.86	1	0.95	0.91	1	1.08	E
13	79	25	0.96	1.15	0.94	1.3	1.11	1.06	1.15	1	0.71	1	0.7	1.1	1	0.82	1	1	E
14	73	3	1	1.15	0.94	1.65	1.3	1.56	1.15	1	0.86	1	0.7	1.1	1.07	1.1	1.24	1.23	SD
15	61	3.9	1	1.4	0.94	1.3	1.3	1.06	1.15	0.87	0.86	1.13	0.86	1.21	1.14	0.91	1	1.23	E
16	40	6.1	0.6	1.4	1	1.3	1.3	1.56	1	0.87	0.86	1	0.86	1	1	1	1	1	E
17	9	3.6	0.53	1.4	1	1.3	1.3	1.56	1	0.87	0.86	0.82	0.86	1	1	1	1	1	E
18	11,400	320	1	1.15	1.16	1.15	1.3	1.21	1	1.07	0.86	1	1	1	1	1.24	1.1	1.08	E
19	6,600	1,150	0.84	1.15	1.08	1	1.11	1.21	0.87	0.94	0.71	0.91	1	1	1	0.91	0.91	1	E
20	6,400	299	0.96	1.4	1.08	1.3	1.11	1.21	1.15	1.07	0.71	0.82	1.08	1.1	1.07	1.24	1	1.08	SD
21	2,455	252	1	1	1.16	1.15	1.06	1.14	0.87	0.87	0.86	1	1	1	1	0.91	0.91	1	E
22	724	118	0.92	1.15	1	1	1.27	1.06	1	1	0.86	0.82	0.86	0.9	1	0.91	1	1.23	E
23	539	77	0.98	1.15	1	1	1.08	1.06	1	1	0.86	0.82	0.86	0.9	1	1	1	1.23	E
24	453	90	1	0.88	1	0.85	1.06	1.06	1	0.87	1	1.29	1	1.1	0.95	0.82	0.83	1	SD

25	523	38	1	1.15	1.16	1.3	1.15	1.06	1	0.87	0.86	1	0.86	1.1	1	0.82	0.91	1.08	E
26	387	48	1	0.94	1	0.85	1.07	1.06	1.15	1.07	0.86	1	0.86	1.1	1	0.91	1.1	1.08	E
27	88	9.4	1	1.15	0.94	1.15	1.35	1.21	1	0.87	1	1	1	1	1	0.82	1.1	1.08	E
28	98	13	1	1.15	1.08	1.3	1.11	1.21	1.15	1.07	0.86	1	0.86	1.1	1.07	1.1	1.1	1	ORG
29	7.3	2.14	1	0.88	1	1	1	1	1	1	1.1	1.29	0.86	1	1	0.91	0.91	1.23	SD
30	5.9	1.98	1	0.88	1	1	1	1	1	1	1	1.29	0.86	1	1	0.91	0.91	1.23	SD
31	1,063	62	0.81	1.4	1.08	1	1.48	1.56	1.15	1.07	0.86	0.82	0.86	1.1	1.07	1	1	1	E
32	702	390	0.67	0.88	1.08	0.85	1	1	1	1	0.71	0.82	1	1	1	1.1	1.1	1	SD
33	605	42	0.96	1.4	1.08	1.3	1.48	1.56	1.15	0.94	0.86	0.82	0.86	0.9	1	0.91	0.91	1	E
34	230	23	0.96	1.15	1.08	1	1.06	1	1	0.87	1	1	1	1	1	0.91	1.1	1.23	E
35	82	13	1	0.75	0.94	1.3	1.06	1.21	1.15	1	1	0.91	1	1.1	1	1.24	1.24	1	E
36	55	15	0.81	0.88	1.08	0.85	1	1	0.87	0.87	1.19	1	1.17	0.9	0.95	1	0.91	1.04	SD
37	47	60	0.56	0.88	0.94	0.7	1	1.06	1	1	0.86	0.82	0.86	1	1	1	1	1	ORG
38	12	15	1	1	1	1.15	1	1	0.87	0.87	0.71	0.91	1	0.9	0.95	0.82	0.91	1	ORG
39	8	6.2	1	1	1	1.15	1	1	0.87	1	0.71	0.82	0.7	1	0.95	0.91	1.1	1	ORG
40	8	3	0.83	1	0.94	1.3	1	1	1	0.87	0.86	0.82	1.17	1	1	1.1	1	1	ORG
41	6	5.3	1	0.88	0.94	1	1	1	0.87	0.87	1	0.82	0.7	0.9	0.95	0.91	0.91	1	ORG
42	45	45.5	0.43	0.88	1.04	1.07	1	1.06	0.87	1.07	0.86	1	0.93	0.9	0.95	0.95	0.95	1.04	ORG
43	83	28.6	0.98	1	1.04	1.07	1	1.21	0.87	1.07	0.86	1	1	0.9	0.95	1	1	1.04	ORG
44	87	30.6	0.98	0.88	1.04	1.07	1.06	1.21	0.87	1.07	1	1	1	0.9	0.95	1.1	1	1.04	ORG
45	106	35	0.91	0.88	1.04	1.07	1	1.06	0.87	1.07	1	1	1	0.9	0.95	1	0.95	1.04	ORG
46	126	73	0.78	0.88	1.04	1.07	1	1.06	0.87	1.07	1	1	0.86	0.9	0.95	1	1	1.04	ORG
47	36	23	1	0.75	0.94	1.3	1	1	0.87	0.87	0.71	0.82	0.7	1.1	1.07	1.1	1	1.04	ORG
48	1,272	464	0.67	0.88	0.94	0.85	1	1	0.87	1	1.19	0.91	1.17	0.9	0.95	1.1	1	1.04	SD
49	156	91	1	1	1	0.85	1	1	1	0.87	0.71	1	0.7	1.1	1	0.82	0.91	1	SD
50	176	24	1	1.15	1	1	1.3	1.21	1	0.87	0.86	1	0.86	1.1	1	1	1	1	E
51	122	10	1	0.88	1	1	1	1	1	1.15	1.19	1	1.42	1	0.95	1.24	1.1	1.04	ORG
52	41	8.2	1	0.88	0.94	0.85	1	1.06	1.15	1	1	1	1	1.1	1.07	1.24	1.1	1	ORG
53	14	5.3	1	0.88	0.94	1.15	1.11	1.21	1.3	1	0.71	1	0.7	1.1	1.07	1	1.1	1.08	SD
54	20	4.4	1	1	0.94	1	1	1.06	1.15	0.87	1	0.82	1	1	0.95	0.91	1.1	1	ORG
55	18	6.3	1	0.88	0.94	0.7	1	1	0.87	0.87	0.86	0.82	1.17	0.9	0.95	1.1	1	1	ORG
56	958	27	1	1.15	0.94	1.3	1.3	1.21	1	1	0.86	0.91	1	1.1	1.07	1.1	1.1	1.08	E
57	237	17	0.87	1	0.94	1.15	1.11	1.21	1.3	1	1	1	1	1.1	1.07	1.1	1.1	1.23	E

58	130	25	1	1.4	0.94	1.3	1.66	1.21	1	1	0.71	0.82	0.7	0.9	0.95	0.91	1	1	E
59	70	23	0.9	1	0.94	1.15	1.06	1.06	1	0.87	1	1	1	1	1	0.91	1	1	ORG
60	57	6.7	1	1.15	0.94	1.3	1.11	1.06	1	1	0.86	1.13	0.86	1.1	1.07	1.1	1.1	1.08	ORG
61	50	28	1	1	0.94	1.15	1	1	0.87	0.87	0.86	1	0.86	0.9	1	0.82	1	1	ORG
62	38	9.1	1	0.88	0.94	1.3	1.11	1.21	1.15	1	0.78	0.82	0.7	1.21	1.14	0.91	1.24	1	SD
63	15	10	1	1	0.94	1.15	1	1	1	0.87	0.71	0.82	0.86	1	1	0.82	1	1	E

APPENDIX B

COCOMO Cost Driver Table (Boehm, 1981, pg. 118)

	VLOW	LOW	NOM	HIGH	VHIGH	EHIGH
RELY	0.75	0.88	1.00	1.15	1.4	
DATA		0.94	1	1.08	1.16	
CPLX	0.70	0.85	1.00	1.15	1.30	1.65
TIME			1.00	1.11	1.30	1.66
STOR			1.00	1.06	1.21	1.56
VIRT		0.87	1.00	1.15	1.30	
TURN		0.87	1.00	1.07	1.15	
ACAP	1.46	1.19	1.00	0.86	0.71	
AEXP	1.29	1.13	1.00	0.91	0.82	
PCAP	1.42	1.17	1.00	0.86	0.70	
VEXP	1.21	1.10	1.00	0.9		
LEXP	1.14	1.07	1.00	0.95		
MODP	1.24	1.10	1.00	0.91	0.82	
TOOL	1.24	1.10	1.00	0.91	0.83	
SCED	1.23	1.08	1.00	1.04	1.10	

APPENDIX C

Kemmerer Data Set

Project	MM ACT	KDSI	AAF*	RELY	DATA	CPLX	TIME	STOR	VIRT	TURN	ACAP	AEXP	PCAP	VEXP	LEXP	MODP	TOOL	SCED	MODE
1	287	253.6	1	1.15	1.08	1.15	1	1.06	0.87	1	0.86	1.13	0.86	1	1	0.82	0.91	1.02	SD
2	82.5	40.5	1	1	1	1	1	1	0.87	1	1	1.07	0.86	1	1	1	1	1	SD
3	1,107.31	450	1	1	1.16	1	1.3	1.21	0.87	1	0.86	1.13	1	1	1.03	0.91	1	1	E
4	86.9	214.4	1	1	1.08	0.92	1	1	0.87	0.93	0.8	0.89	0.85	0.97	0.95	1	1	1.02	SD
5	336.3	449.9	1	1	0.94	1	1	1	0.93	0.87	0.78	1.13	0.93	1.1	1.03	1	0.91	1.07	ORG
6	84	50	1	1	1.16	1	1.11	1.06	1	0.87	0.86	1.13	0.86	0.95	0.97	0.91	1	1.23	E
7	23.2	43	1	1	1.16	1	1.11	1.06	1	0.87	0.86	1.13	0.7	0.95	1.07	0.91	1	1.23	E
8	130.3	167	1	1.15	1.16	1	1	1	1	0.93	1	0.95	1	0.95	0.97	1	1	1.16	SD
9	116	289	1	1	1.16	1.15	1.11	1.06	0.87	0.87	1	1.13	1.06	1.1	1	1	1	1.08	E
10	72	39	1	1	1.16	1	1.11	1	0.93	1.03	0.71	1	0.7	1.1	1.14	1.05	1	1.23	SD
11	258.7	254.2	1	1.16	1	1	1	1	1	1	0.86	1.13	0.86	1	1	0.86	1	1.23	SD
12	230.7	128.6	1	1	1.16	1	1	1	0.87	0.87	0.86	1.07	0.86	1	1.03	1.1	0.95	1.08	SD
13	157	161.4	1	1	1.16	1	1.06	1	0.87	0.87	1.19	1	0.78	1.21	0.97	1.1	1	1.08	SD
14	246.9	164.8	1	1	1.16	1	1	1	0.87	0.87	0.86	1.21	0.93	1.1	1.1	0.95	0.91	1.04	ORG
15	69.9	60.2	1	1	1	1	1	1	1	0.87	0.71	0.91	0.86	1.1	1.03	0.91	0.91	1	SD

* AAF values assumed, no values given by Kemmerer

APPENDIX D

COCOMO TRAINING AND TESTING DATA SETS

TRAINING DATA SET

Project	MM ACTUAL	TOT KDSI	AAF	RELY	DATA	CPLX	TIME	STOR	VIRT	TURN	ACAP	AEXP	PCAP	VEXP	LEXP	MODP	TOOL	SCED	MODE
1	2,040	113	1	0.88	1.16	0.7	1	1.06	1.15	1.07	1.19	1.13	1.17	1.1	1	1.24	1.1	1.04	E
3	243	132	1	1	1.16	0.85	1	1	0.87	0.94	0.86	0.82	0.86	0.9	0.95	0.91	0.91	1	SD
4	240	60	0.76	0.75	1.16	0.7	1	1	0.87	1	1.19	0.91	1.42	1	0.95	1.24	1	1.04	ORG
5	33	16	1	0.88	0.94	1	-1	1	0.87	1	1	1	0.86	0.9	0.95	1.24	1	1	ORG
9	423	30	1	1.15	0.94	1.3	1.3	1.21	1.15	1	0.86	1	0.86	1.1	1.07	0.91	1	1	E
10	321	29	0.63	1.4	0.94	1.3	1.11	1.56	1	1.07	0.86	0.82	0.86	0.9	1	1	1	1	E
11	218	32	0.63	1.4	0.94	1.3	1.11	1.56	1	1.07	0.86	0.82	0.86	0.9	1	1	1	1	E
16	40	6.1	0.6	1.4	1	1.3	1.3	1.56	1	0.87	0.86	1	0.86	1	1	1	1	1	E
20	6,400	299	0.96	1.4	1.08	1.3	1.11	1.21	1.15	1.07	0.71	0.82	1.08	1.1	1.07	1.24	1	1.08	SD
21	2,455	252	1	1	1.16	1.15	1.06	1.14	0.87	0.87	0.86	1	1	1	1	0.91	0.91	1	E
22	724	118	0.92	1.15	1	1	1.27	1.06	1	1	0.86	0.82	0.86	0.9	1	0.91	1	1.23	E
23	539	77	0.98	1.15	1	1	1.08	1.06	1	1	0.86	0.82	0.86	0.9	1	1	1	1.23	E
24	453	90	1	0.88	1	0.85	1.06	1.06	1	0.87	1	1.29	1	1.1	0.95	0.82	0.83	1	SD
25	523	38	1	1.15	1.16	1.3	1.15	1.06	1	0.87	0.86	1	0.86	1.1	1	0.82	0.91	1.08	E
26	387	48	1	0.94	1	0.85	1.07	1.06	1.15	1.07	0.86	1	0.86	1.1	1	0.91	1.1	1.08	E
28	98	13	1	1.15	1.08	1.3	1.11	1.21	1.15	1.07	0.86	1	0.86	1.1	1.07	1.1	1.1	1	ORG
31	1,063	62	0.81	1.4	1.08	1	1.48	1.56	1.15	1.07	0.86	0.82	0.86	1.1	1.07	1	1	1	E
32	702	390	0.67	0.88	1.08	0.85	1	1	1	1	0.71	0.82	1	1	1	1.1	1.1	1	SD
33	605	42	0.96	1.4	1.08	1.3	1.48	1.56	1.15	0.94	0.86	0.82	0.86	0.9	1	0.91	0.91	1	E
34	230	23	0.96	1.15	1.08	1	1.06	1	1	0.87	1	1	1	1	1	0.91	1.1	1.23	E
35	82	13	1	0.75	0.94	1.3	1.06	1.21	1.15	1	1	0.91	1	1.1	1	1.24	1.24	1	E
36	55	15	0.81	0.88	1.08	0.85	1	1	0.87	0.87	1.19	1	1.17	0.9	0.95	1	0.91	1.04	SD

40	8	3	0.83	1	0.94	1.3	1	1	1	0.87	0.86	0.82	1.17	1	1	1.1	1	1	ORG
41	6	5.3	1	0.88	0.94	1	1	1	0.87	0.87	1	0.82	0.7	0.9	0.95	0.91	0.91	1	ORG
42	45	45.5	0.43	0.88	1.04	1.07	1	1.06	0.87	1.07	0.86	1	0.93	0.9	0.95	0.95	0.95	1.04	ORG
43	83	28.6	0.98	1	1.04	1.07	1	1.21	0.87	1.07	0.86	1	1	0.9	0.95	1	1	1.04	ORG
44	87	30.6	0.98	0.88	1.04	1.07	1.06	1.21	0.87	1.07	1	1	1	0.9	0.95	1.1	1	1.04	ORG
45	106	35	0.91	0.88	1.04	1.07	1	1.06	0.87	1.07	1	1	1	0.9	0.95	1	0.95	1.04	ORG
46	126	73	0.78	0.88	1.04	1.07	1	1.06	0.87	1.07	1	1	0.86	0.9	0.95	1	1	1.04	ORG
47	36	23	1	0.75	0.94	1.3	1	1	0.87	0.87	0.71	0.82	0.7	1.1	1.07	1.1	1	1.04	ORG
48	1,272	464	0.67	0.88	0.94	0.85	1	1	0.87	1	1.19	0.91	1.17	0.9	0.95	1.1	1	1.04	SD
49	156	91	1	1	1	0.85	1	1	1	0.87	0.71	1	0.7	1.1	1	0.82	0.91	1	SD
50	176	24	1	1.15	1	1	1.3	1.21	1	0.87	0.86	1	0.86	1.1	1	1	1	1	E
51	122	10	1	0.88	1	1	1	1	1	1.15	1.19	1	1.42	1	0.95	1.24	1.1	1.04	ORG
53	14	5.3	1	0.88	0.94	1.15	1.11	1.21	1.3	1	0.71	1	0.7	1.1	1.07	1	1.1	1.08	SD
54	20	4.4	1	1	0.94	1	1	1.06	1.15	0.87	1	0.82	1	1	0.95	0.91	1.1	1	ORG
55	18	6.3	1	0.88	0.94	0.7	1	1	0.87	0.87	0.86	0.82	1.17	0.9	0.95	1.1	1	1	ORG
56	958	27	1	1.15	0.94	1.3	1.3	1.21	1	1	0.86	0.91	1	1.1	1.07	1.1	1.1	1.08	E
57	237	17	0.87	1	0.94	1.15	1.11	1.21	1.3	1	1	1	1	1.1	1.07	1.1	1.1	1.23	E
58	130	25	1	1.4	0.94	1.3	1.66	1.21	1	1	0.71	0.82	0.7	0.9	0.95	0.91	1	1	E
62	38	9.1	1	0.88	0.94	1.3	1.11	1.21	1.15	1	0.78	0.82	0.7	1.21	1.14	0.91	1.24	1	SD
63	15	10	1	1	0.94	1.15	1	1	1	0.87	0.71	0.82	0.86	1	1	0.82	1	1	E

COCOMO TESTING DATA SET

Project	MMACTUAL	TOTKDSI	AAF	RELY	DATA	CPLX	TIME	STOR	VIRT	TURN	ACAP	AEXP	PCAP	VEXP	LEXP	MODP	TOOL	SCED	MODE
2	1,600	293	0.85	0.88	1.16	0.85	1	1.06	1	1.07	1	0.91	1	0.9	0.95	1.1	1	1	E
6	43	4	1	0.75	1	0.85	1	1.21	1	1	1.46	1	1.42	0.9	0.95	1.24	1.1	1	ORG
7	8	6.9	1	0.75	1	1	1	1	0.87	0.87	1	1	1	0.9	0.95	0.91	0.91	1	ORG
8	1,075	22	1	1.15	0.94	1.3	1.66	1.56	1.3	1	0.71	0.91	1	1.21	1.14	1.1	1.1	1.08	E
12	201	37	1	1.15	0.94	1.3	1.11	1.06	1	1	0.86	0.82	0.86	1	0.95	0.91	1	1.08	E
13	79	25	0.96	1.15	0.94	1.3	1.11	1.06	1.15	1	0.71	1	0.7	1.1	1	0.82	1	1	E
14	73	3	1	1.15	0.94	1.65	1.3	1.56	1.15	1	0.86	1	0.7	1.1	1.07	1.1	1.24	1.23	SD
15	61	3.9	1	1.4	0.94	1.3	1.3	1.06	1.15	0.87	0.86	1.13	0.86	1.21	1.14	0.91	1	1.23	E
17	9	3.6	0.53	1.4	1	1.3	1.3	1.56	1	0.87	0.86	0.82	0.86	1	1	1	1	1	E
18	11,400	320	1	1.15	1.16	1.15	1.3	1.21	1	1.07	0.86	1	1	1	1	1.24	1.1	1.08	E
19	6,600	1,150	0.84	1.15	1.08	1	1.11	1.21	0.87	0.94	0.71	0.91	1	1	1	0.91	0.91	1	E
27	88	9.4	1	1.15	0.94	1.15	1.35	1.21	1	0.87	1	1	1	1	1	0.82	1.1	1.08	E
29	7.3	2.14	1	0.88	1	1	1	1	1	1	1.1	1.29	0.86	1	1	0.91	0.91	1.23	SD
30	5.9	1.98	1	0.88	1	1	1	1	1	1	1	1.29	0.86	1	1	0.91	0.91	1.23	SD
37	47	60	0.56	0.88	0.94	0.7	1	1.06	1	1	0.86	0.82	0.86	1	1	1	1	1	ORG
38	12	15	1	1	1	1.15	1	1	0.87	0.87	0.71	0.91	1	0.9	0.95	0.82	0.91	1	ORG
39	8	6.2	1	1	1	1.15	1	1	0.87	1	0.71	0.82	0.7	1	0.95	0.91	1.1	1	ORG
52	41	8.2	1	0.88	0.94	0.85	1	1.06	1.15	1	1	1	1	1.1	1.07	1.24	1.1	1	ORG
59	70	23	0.9	1	0.94	1.15	1.06	1.06	1	0.87	1	1	1	1	1	0.91	1	1	ORG
60	57	6.7	1	1.15	0.94	1.3	1.11	1.06	1	1	0.86	1.13	0.86	1.1	1.07	1.1	1.1	1.08	ORG
61	50	28	1	1	0.94	1.15	1	1	0.87	0.87	0.86	1	0.86	0.9	1	0.82	1	1	ORG

APPENDIX E

BrainMaker Neural Network Definition Files (*.DEF)

COCOMO Training/Kemmerer Testing Version

****

Network 5/8

```
input number 1 20
dictionary input  LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
 ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED E SD ORG
output number 1 1
dictionary output  LOG_MMAC
hidden 5 8
filename trainfacts c:\brain\test\cokeall1.fct
filename runfacts c:\brain\test\kemmer.in
learnrate 0.9000 50 0.75 75 0.6000 90 0.5000
learnlayer 1.0000 1.0000 1.0000
traintol 0.1000 0.04 0.8000 100
testtol 0.2000
random 5.0
maxruns 459
function hidden1 sigmoid 0.0000 1.0000 0.0000 1.00000
function hidden2 sigmoid 0.0000 1.0000 0.0000 1.00000
function output sigmoid 0.0000 1.0000 0.0000 1.00000
 LOG_KDS  AAF  RELY  DATA  CPLX  TIME  STOR  VIRT  TURN
ACAP  AEXP  PCAP  VEXP  LEXP  MODP  TOOL  SCED  E  SD
ORG
 LOG_MMA
scale input minimum
0.29666  0.43  0.75  0.94  0.7  1  1  0.87  0.87  0.71  0.82  0.7  0.9
 0.95  0.82  0.83  1 0 0 0
scale input maximum
3.06069  1  1.4  1.16  1.65  1.66  1.56  1.3  1.15  1.46  1.29  1.42  1.21
  1.14  1.24  1.24  1.23  1 1 1
scale output minimum
0.77085
scale output maximum
 4.0569
```

****

Network 8/9

****

```
input number 1 20
dictionary input  LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
 ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED E SD ORG
output number 1 1
dictionary output  LOG_MMAC
hidden 8 9
filename trainfacts c:\brain\test\cokeall1.fct
filename runfacts c:\brain\test\kemmer.in
learnrate 0.9000 50 0.75 75 0.6000 90 0.5000
learnlayer 1.0000 1.0000 1.0000
traintol 0.1000 0.04 0.8000 100
testtol 0.2000
random 5.0
maxruns 430
function hidden1 sigmoid 0.0000 1.0000 0.0000 1.00000
function hidden2 sigmoid 0.0000 1.0000 0.0000 1.00000
function output sigmoid 0.0000 1.0000 0.0000 1.00000
 LOG_KDS  AAF  RELY  DATA  CPLX  TIME  STOR  VIRT  TURN
ACAP  AEXP  PCAP  VEXP  LEXP  MODP  TOOL  SCED  E  SD
ORG
 LOG_MMA
scale input minimum
0.29666  0.43  0.75  0.94  0.7  1  1  0.87  0.87  0.71  0.82  0.7  0.9
 0.95  0.82  0.83  1 0 0 0
scale input maximum
3.06069  1  1.4  1.16  1.65  1.66  1.56  1.3  1.15  1.46  1.29  1.42  1.21
  1.14  1.24  1.24  1.23 1 1 1
scale output minimum
0.77085
scale output maximum
 4.0569
```

****

Network 11/10

****

```
input number 1 20
dictionary input  LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
 ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED E SD ORG
output number 1 1
dictionary output  LOG_MMAC
hidden 11 10
filename trainfacts c:\brain\test\cokeall1.fct
filename runfacts c:\brain\test\kemmer.in
learnrate  0.9000 50  0.75 75  0.6000 90  0.5000
learnlayer  1.0000  1.0000  1.0000
traintol  0.1000  0.04  0.8000 100
testtol  0.2000
random 5.0
maxruns 250
function hidden1 sigmoid  0.0000  1.0000  0.0000 1.00000
function hidden2 sigmoid  0.0000  1.0000  0.0000 1.00000
function output sigmoid  0.0000  1.0000  0.0000 1.00000
 LOG_KDS   AAF   RELY   DATA   CPLX   TIME   STOR   VIRT   TURN
ACAP   AEXP   PCAP   VEXP   LEXP   MODP   TOOL   SCED    E    SD
ORG
 LOG_MMA
scale input minimum
0.29666   0.43   0.75   0.94   0.7    1    1  0.87   0.87   0.71   0.82   0.7   0.9
 0.95   0.82   0.83     1 0 0 0
scale input maximum
3.06069     1    1.4   1.16   1.65   1.66   1.56   1.3   1.15   1.46   1.29   1.42   1.21
  1.14   1.24   1.24   1.23  1 1 1
scale output minimum
0.77085
scale output maximum
 4.0569
```

****

Network 16/19

****

```
input number 1 20
dictionary input  LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
 ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED E SD ORG
output number 1 1
dictionary output  LOG_MMAC
hidden 16 19
filename trainfacts c:\brain\test\cokeall1.fct
filename runfacts c:\brain\test\kemmer.in
learnrate  0.9000 50  0.75 75  0.6000 90  0.5000
learnlayer  1.0000  1.0000  1.0000
traintol  0.1000  0.04  0.8000 100
testtol  0.2000
random 5.0
maxruns 304
function hidden1 sigmoid  0.0000  1.0000  0.0000 1.00000
function hidden2 sigmoid  0.0000  1.0000  0.0000 1.00000
function output sigmoid  0.0000  1.0000  0.0000 1.00000
 LOG_KDS   AAF   RELY   DATA   CPLX   TIME   STOR   VIRT   TURN
ACAP   AEXP   PCAP   VEXP   LEXP   MODP   TOOL   SCED    E    SD
ORG
 LOG_MMA
scale input minimum
0.29666   0.43   0.75   0.94    0.7     1     1   0.87   0.87   0.71   0.82   0.7    0.9
 0.95   0.82   0.83      1  0 0 0
scale input maximum
3.06069     1    1.4   1.16   1.65   1.66   1.56    1.3   1.15   1.46   1.29   1.42   1.21
  1.14   1.24   1.24   1.23  1 1 1
scale output minimum
0.77085
scale output maximum
 4.0569
```

****

Network 18/15

****

```
input number 1 20
dictionary input  LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
 ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED E SD ORG
output number 1 1
dictionary output  LOG_MMAC
hidden 18 15
filename trainfacts c:\brain\test\cokeall1.fct
filename runfacts c:\brain\test\kemmer.in
learnrate  0.9000 50  0.75 75  0.6000 90  0.5000
learnlayer  1.0000  1.0000  1.0000
traintol  0.1000  0.04  0.8000 100
testtol  0.2000
random 5.0
maxruns 318
function hidden1 sigmoid  0.0000  1.0000  0.0000 1.00000
function hidden2 sigmoid  0.0000  1.0000  0.0000 1.00000
function output sigmoid  0.0000  1.0000  0.0000 1.00000
 LOG_KDS   AAF  RELY  DATA  CPLX  TIME  STOR  VIRT  TURN
ACAP  AEXP  PCAP  VEXP  LEXP  MODP  TOOL  SCED   E   SD
ORG
 LOG_MMA
scale input minimum
0.29666  0.43  0.75  0.94  0.7   1   1  0.87  0.87  0.71  0.82  0.7  0.9
 0.95  0.82  0.83   1 0 0 0
scale input maximum
3.06069   1   1.4  1.16  1.65  1.66  1.56  1.3  1.15  1.46  1.29  1.42  1.21
  1.14  1.24  1.24  1.23  1 1 1
scale output minimum
0.77085
scale output maximum
 4.0569
```

****

Network 24/25

****

```
input number 1 20
dictionary input  LOG_KDSI AAF RELY DATA CPLX TIME STOR VIRT TURN
 ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED E SD ORG
output number 1 1
dictionary output  LOG_MMAC
hidden 24 25
filename trainfacts c:\brain\test\cokeall1.fct
filename runfacts c:\brain\test\kemmer.in
learnrate 0.9000 50 0.75 75 0.6000 90 0.5000
learnlayer 1.0000 1.0000 1.0000
traintol 0.1000 0.04 0.8000 100
testtol 0.2000
random 5.0
maxruns 417
function hidden1 sigmoid 0.0000 1.0000 0.0000 1.00000
function hidden2 sigmoid 0.0000 1.0000 0.0000 1.00000
function output sigmoid 0.0000 1.0000 0.0000 1.00000
 LOG_KDS  AAF  RELY  DATA  CPLX  TIME  STOR  VIRT  TURN
ACAP  AEXP  PCAP  VEXP  LEXP  MODP  TOOL  SCED  E  SD
ORG
 LOG_MMA
scale input minimum
0.29666  0.43  0.75  0.94  0.7  1  1  0.87  0.87  0.71  0.82  0.7  0.9
 0.95  0.82  0.83  1 0 0 0
scale input maximum
3.06069  1  1.4  1.16  1.65  1.66  1.56  1.3  1.15  1.46  1.29  1.42  1.21
  1.14  1.24  1.24  1.23 1 1 1
scale output minimum
0.77085
scale output maximum
 4.0569
```

****

COKEALL1.FCT

****

facts
------- 1
2.05307 1 0.88 1.16 0.7 1 1.06 1.15 1.07 1.19 1.13 1.17 1.1
1 1.24 1.1 1.04 [E
3.30963
------- 2
2.46686 0.85 0.88 1.16 0.85 1 1.06 1 1.07 1 0.91 1 0.9
0.95 1.1 1 1 [E
3.20412
------- 3
2.12057 1 1 1.16 0.85 1 1 0.87 0.94 0.86 0.82 0.86 0.9
0.95 0.91 0.91 1 [SD
2.3856
------- 4
1.77815 0.76 0.75 1.16 0.7 1 1 0.87 1 1.19 0.91 1.42 1
0.95 1.24 1 1.04 [ORG
2.38021
------- 5
1.20412 1 0.88 0.94 1 1 1 0.87 1 1 1 0.86 0.9
0.95 1.24 1 1 [ORG
1.51851
------- 6
0.60206 1 0.75 1 0.85 1 1.21 1 1 1.46 1 1.42 0.9
0.95 1.24 1.1 1 [ORG
1.63346
------- 7
0.83884 1 0.75 1 1 1 1 0.87 0.87 1 1 1 0.9 0.95
0.91 0.91 1 [ORG
0.90309
------- 8
1.34242 1 1.15 0.94 1.3 1.66 1.56 1.3 1 0.71 0.91 1 1.21
1.14 1.1 1.1 1.08 [E
3.0314
------- 9

1.47712 1 1.15 0.94 1.3 1.3 1.21 1.15 1 0.86 1 0.86 1.1
1.07 0.91 1 1 [E
2.62634
-------- 10
1.46239 0.63 1.4 0.94 1.3 1.11 1.56 1 1.07 0.86 0.82 0.86 0.9
1 1 1 1 [E
2.5065
-------- 11
1.50515 0.63 1.4 0.94 1.3 1.11 1.56 1 1.07 0.86 0.82 0.86 0.9
1 1 1 1 [E
2.33845
-------- 12
1.5682 1 1.15 0.94 1.3 1.11 1.06 1 1 0.86 0.82 0.86 1
0.95 0.91 1 1.08 [E
2.30319
-------- 13
1.39794 0.96 1.15 0.94 1.3 1.11 1.06 1.15 1 0.71 1 0.7 1.1
1 0.82 1 1 [E
1.89762
-------- 14
0.47712 1 1.15 0.94 1.65 1.3 1.56 1.15 1 0.86 1 0.7 1.1
1.07 1.1 1.24 1.23 [SD
1.86332
-------- 15
0.59106 1 1.4 0.94 1.3 1.3 1.06 1.15 0.87 0.86 1.13 0.86 1.21
1.14 0.91 1 1.23 [E
1.78533
-------- 16
0.78533 0.6 1.4 1 1.3 1.3 1.56 1 0.87 0.86 1 0.86 1
1 1 1 1 [E
1.60206
-------- 17
0.5563 0.53 1.4 1 1.3 1.3 1.56 1 0.87 0.86 0.82 0.86 1
1 1 1 1 [E
0.95424
-------- 18
2.50515 1 1.15 1.16 1.15 1.3 1.21 1 1.07 0.86 1 1 1
1 1.24 1.1 1.08 [E
4.0569
-------- 19
3.06069 0.84 1.15 1.08 1 1.11 1.21 0.87 0.94 0.71 0.91 1 1
1 0.91 0.91 1 [E
3.81954

-------- 20
2.47567 0.96 1.4 1.08 1.3 1.11 1.21 1.15 1.07 0.71 0.82 1.08
1.1 1.07 1.24 1 1.08 [SD
3.80618
-------- 21
2.4014 1 1 1.16 1.15 1.06 1.14 0.87 0.87 0.86 1 1 1
1 0.91 0.91 1 [E
3.39005
-------- 22
2.07188 0.92 1.15 1 1 1.27 1.06 1 1 0.86 0.82 0.86 0.9
1 0.91 1 1.23 [E
2.85973
-------- 23
1.88649 0.98 1.15 1 1 1.08 1.06 1 1 0.86 0.82 0.86 0.9
1 1 1 1.23 [E
2.73158
-------- 24
1.95424 1 0.88 1 0.85 1.06 1.06 1 0.87 1 1.29 1 1.1
0.95 0.82 0.83 1 [SD
2.65609
-------- 25
1.57978 1 1.15 1.16 1.3 1.15 1.06 1 0.87 0.86 1 0.86 1.1
1 0.82 0.91 1.08 [E
2.7185
-------- 26
1.68124 1 0.94 1 0.85 1.07 1.06 1.15 1.07 0.86 1 0.86 1.1
1 0.91 1.1 1.08 [E
2.58771
-------- 27
0.97312 1 1.15 0.94 1.15 1.35 1.21 1 0.87 1 1 1 1
1 0.82 1.1 1.08 [E
1.94448
-------- 28
1.11394 1 1.15 1.08 1.3 1.11 1.21 1.15 1.07 0.86 1 0.86 1.1
1.07 1.1 1.1 1 [ORG
1.99122
-------- 29
0.33041 1 0.88 1 1 1 1 1 1 1.1 1.29 0.86 1 1
0.91 0.91 1.23 [SD
0.86332
-------- 30
0.29666 1 0.88 1 1 1 1 1 1 1 1.29 0.86 1 1
0.91 0.91 1.23 [SD

0.77085
-------- 31
1.79239 0.81 1.4 1.08 1 1.48 1.56 1.15 1.07 0.86 0.82 0.86 1.1
1.07 1 1 1 [E
3.02653
-------- 32
2.59106 0.67 0.88 1.08 0.85 1 1 1 1 0.71 0.82 1 1
1 1.1 1.1 1 [SD
2.84633
-------- 33
1.62324 0.96 1.4 1.08 1.3 1.48 1.56 1.15 0.94 0.86 0.82 0.86
0.9 1 0.91 0.91 1 [E
2.78175
-------- 34
1.36172 0.96 1.15 1.08 1 1.06 1 1 0.87 1 1 1 1 1
0.91 1.1 1.23 [E
2.36172
-------- 35
1.11394 1 0.75 0.94 1.3 1.06 1.21 1.15 1 1 0.91 1 1.1
1 1.24 1.24 1 [E
1.91381
-------- 36
1.17609 0.81 0.88 1.08 0.85 1 1 0.87 0.87 1.19 1 1.17 0.9
0.95 1 0.91 1.04 [SD
1.74036
-------- 37
1.77815 0.56 0.88 0.94 0.7 1 1.06 1 1 0.86 0.82 0.86 1
1 1 1 1 [ORG
1.67209
-------- 38
1.17609 1 1 1 1.15 1 1 0.87 0.87 0.71 0.91 1 0.9
0.95 0.82 0.91 1 [ORG
1.07918
-------- 39
0.79239 1 1 1 1.15 1 1 0.87 1 0.71 0.82 0.7 1
0.95 0.91 1.1 1 [ORG
0.90309
-------- 40
0.47712 0.83 1 0.94 1.3 1 1 1 0.87 0.86 0.82 1.17 1
1 1.1 1 1 [ORG
0.90309
-------- 41

0.72427 1 0.88 0.94 1 1 1 0.87 0.87 1 0.82 0.7 0.9
0.95 0.91 0.91 1 [ORG
0.77815
-------- 42
1.65801 0.43 0.88 1.04 1.07 1 1.06 0.87 1.07 0.86 1 0.93 0.9
0.95 0.95 0.95 1.04 [ORG
1.65321
-------- 43
1.45636 0.98 1 1.04 1.07 1 1.21 0.87 1.07 0.86 1 1 0.9
0.95 1 1 1.04 [ORG
1.91907
-------- 44
1.48572 0.98 0.88 1.04 1.07 1.06 1.21 0.87 1.07 1 1 1 0.9
0.95 1.1 1 1.04 [ORG
1.93951
-------- 45
1.54406 0.91 0.88 1.04 1.07 1 1.06 0.87 1.07 1 1 1 0.9
0.95 1 0.95 1.04 [ORG
2.0253
-------- 46
1.86332 0.78 0.88 1.04 1.07 1 1.06 0.87 1.07 1 1 0.86 0.9
0.95 1 1 1.04 [ORG
2.10037
-------- 47
1.36172 1 0.75 0.94 1.3 1 1 0.87 0.87 0.71 0.82 0.7 1.1
1.07 1.1 1 1.04 [ORG
1.5563
-------- 48
2.66651 0.67 0.88 0.94 0.85 1 1 0.87 1 1.19 0.91 1.17 0.9
0.95 1.1 1 1.04 [SD
3.10448
-------- 49
1.95904 1 1 1 0.85 1 1 1 0.87 0.71 1 0.7 1.1 1
0.82 0.91 1 [SD
2.19312
-------- 50
1.38021 1 1.15 1 1 1.3 1.21 1 0.87 0.86 1 0.86 1.1
1 1 1 1 [E
2.24551
-------- 51
1 1 0.88 1 1 1 1 1 1.15 1.19 1 1.42 1 0.95
1.24 1.1 1.04 [ORG
2.08636

-------- 52
0.91381 1 0.88 0.94 0.85 1 1.06 1.15 1 1 1 1 1.1
1.07 1.24 1.1 1 [ORG
1.61278
-------- 53
0.72427 1 0.88 0.94 1.15 1.11 1.21 1.3 1 0.71 1 0.7 1.1
1.07 1 1.1 1.08 [SD
1.14612
-------- 54
0.64345 1 1 0.94 1 1 1.06 1.15 0.87 1 0.82 1 1
0.95 0.91 1.1 1 [ORG
1.30103
-------- 55
0.79934 1 0.88 0.94 0.7 1 1 0.87 0.87 0.86 0.82 1.17 0.9
0.95 1.1 1 1 [ORG
1.25527
-------- 56
1.43136 1 1.15 0.94 1.3 1.3 1.21 1 1 0.86 0.91 1 1.1
1.07 1.1 1.1 1.08 [E
2.98136
-------- 57
1.23044 0.87 1 0.94 1.15 1.11 1.21 1.3 1 1 1 1 1.1
1.07 1.1 1.1 1.23 [E
2.37474
-------- 58
1.39794 1 1.4 0.94 1.3 1.66 1.21 1 1 0.71 0.82 0.7 0.9
0.95 0.91 1 1 [E
2.11394
-------- 59
1.36172 0.9 1 0.94 1.15 1.06 1.06 1 0.87 1 1 1 1
1 0.91 1 1 [ORG
1.84509
-------- 60
0.82607 1 1.15 0.94 1.3 1.11 1.06 1 1 0.86 1.13 0.86 1.1
1.07 1.1 1.1 1.08 [ORG
1.75587
-------- 61
1.44715 1 1 0.94 1.15 1 1 0.87 0.87 0.86 1 0.86 0.9
1 0.82 1 1 [ORG
1.69897
-------- 62
0.95904 1 0.88 0.94 1.3 1.11 1.21 1.15 1 0.78 0.82 0.7 1.21
1.14 0.91 1.24 1 [SD

1.57978
-------- 63
1 1 1 0.94 1.15 1 1 1 0.87 0.71 0.82 0.86 1 1
0.82 1 1 [E
1.17609
****

KEMMER.IN

****

LOG_KDS AAF RELY DATA CPLX TIME STOR VIRT TURN
ACAP AEXP PCAP VEXP LEXP MODP TOOL SCED SD E
ORG
facts run
-------- 1
2.40414 1 1.15 1.08 1.15 1 1.06 0.87 1 0.86 1.13 0.86 1
1 0.82 0.91 1.02 [SD
-------- 2
1.60745 1 1 1 1 1 1 0.87 1 1 1.07 0.86 1 1
1 1 1 [SD
-------- 3
2.65321 1 1 1.16 1 1.3 1.21 0.87 1 0.86 1.13 1 1
1.03 0.91 1 1 [E
-------- 4
2.33122 1 1 1.08 0.92 1 1 0.87 0.93 0.8 0.89 0.85 0.97
0.95 1 1 1.02 [SD
-------- 5
2.65311 1 1 0.94 1 1 1 0.93 0.87 0.78 1.13 0.93 1.1
1.03 1 0.91 1.07 [ORG
-------- 6
1.69897 1 1 1.16 1 1.11 1.06 1 0.87 0.86 1.13 0.86 0.95
0.97 0.91 1 1.23 [E
-------- 7
1.63346 1 1 1.16 1 1.11 1.06 1 0.87 0.86 1.13 0.7 0.95
1.07 0.91 1 1.23 [E
-------- 8
2.22271 1 1.15 1.16 1 1 1 1 0.93 1 0.95 1 0.95
0.97 1 1 1.16 [SD
-------- 9
2.46089 1 1 1.16 1.15 1.11 1.06 0.87 0.87 1 1.13 1.06 1.1
1 1 1 1.08 [E
-------- 10

1.59106 1 1 1.16 1 1.11 1 0.93 1.03 0.71 1 0.7 1.1
1.14 1.05 1 1.23 [SD
-------- 11
2.40517 1 1.16 1 1 1 1 1 1 0.86 1.13 0.86 1 1
0.86 1 1.23 [SD
-------- 12
2.10924 1 1 1.16 1 1 1 0.87 0.87 0.86 1.07 0.86 1
1.03 1.1 0.95 1.08 [SD
-------- 13
2.2079 1 1 1.16 1 1.06 1 0.87 0.87 1.19 1 0.78 1.21
0.97 1.1 1 1.08 [SD
-------- 14
2.21695 1 1 1.16 1 1 1 0.87 0.87 0.86 1.21 0.93 1.1
1.1 0.95 0.91 1.04 [ORG
-------- 15
1.77959 1 1 1 1 1 1 1 0.87 0.71 0.91 0.86 1.1
1.03 0.91 0.91 1 [SD

APPENDIX F

****

Genetic Algorithm Fitness Function (fit.c)

(Prior to instantiation of awk Wrapper)

****

```
#include <math.h>
struct entry {
 double effort;
 double akdsi;
 int i1,i2,i3,i4,i5,i6,i7,i8,i9,i10,i11,i12,i13,i14,i15;
 int ie;
};

struct entry table[] =
{
#include "table.c"
}
;

int size = (sizeof table)/(sizeof( struct entry));

double f1(y)
register double *y;
{
 double res;
 double emm;
 double exp;
 static double x[96];
 register int i,j;


 for(i = 0; i < 90; i++) {
  x[i] = y[i]+200;
  x[i]/= 400.0;
  x[i] *= 1.5;
  x[i] += .5;
 }
```

Variable Declarations

Dimension Table and Include Fact File "table.c"

Dimension Array of 96 numbers for use by the fitness function.

Constrain cost driver size between 0.5 and 2.0. Constrain coefficients and exponents between 0.0 and 4.0

```
for(i = 90; i < 96; i++) {
  x[i] = y[i] + 200;
  x[i] /= 100;
}

for(res = 0, i= 0; i < 42; i+=6)  {
  if(! (x[i]< x[i+1]))  res +=1000;
  if(! (x[i]< x[i+2]))  res +=1000;
  if(! (x[i]< x[i+3]))  res +=1000;
  if(! (x[i]< x[i+4]))  res +=1000;
  if(! (x[i]< x[i+5]))  res +=1000;
  if(! (x[i+1]< x[i+2]))  res +=1000;
  if(! (x[i+1]< x[i+3]))  res +=1000;
  if(! (x[i+1]< x[i+4]))  res +=1000;
  if(! (x[i+1]< x[i+5]))  res +=1000;
  if(! (x[i+2]< x[i+3]))  res +=1000;
  if(! (x[i+2]< x[i+4]))  res +=1000;
  if(! (x[i+2]< x[i+5]))  res +=1000;
  if(! (x[i+3]< x[i+4]))  res +=1000;
  if(! (x[i+3]< x[i+5]))  res +=1000;
  if(! (x[i+4]< x[i+5]))  res+=1000;
}

for(i=42; i < 84; i+=6)  {
  if(! (x[i]> x[i+1]))  res +=1000;
  if(! (x[i]> x[i+2]))  res +=1000;
  if(! (x[i]> x[i+3]))  res +=1000;
  if(! (x[i]> x[i+4]))  res +=1000;
  if(! (x[i]> x[i+5]))  res +=1000;
  if(! (x[i+1]> x[i+2]))  res +=1000;
  if(! (x[i+1]> x[i+3]))  res +=1000;
  if(! (x[i+1]> x[i+4]))  res +=1000;
  if(! (x[i+1]> x[i+5]))  res +=1000;
  if(! (x[i+2]> x[i+3]))  res +=1000;
  if(! (x[i+2]> x[i+4]))  res +=1000;
  if(! (x[i+2]> x[i+5]))  res +=1000;
  if(! (x[i+3]> x[i+4]))  res +=1000;
  if(! (x[i+3]> x[i+5]))  res +=1000;
  if(! (x[i+4]> x[i+5]))  res+=1000;
}

/* for(i=90; i < 91; i++) {
```

Penalty functions to force GA to obey rules established by Boehm for the first seven cost drivers. Comment out if unconstrained drivers are desired.

Penalty functions to force GA to obey rules established by Boehm for drivers eight through fourteen. Comment out if unconstrained drivers are desired.

```
  if(! (x[i] < x[i+1] )) res +=1000;
  if(! (x[i] < x[i+2] )) res +=1000;
  if(! (x[i+1] < x[i+2])) res +=1000;
 }

for(i=93; i < 94; i++) {
  if(! (x[i] > x[i+1] )) res +=1000;
  if(! (x[i] > x[i+2] )) res +=1000;
  if(! (x[i+1] > x[i+2])) res +=1000;
 }

*/
```

Penalty functions to force GA to obey rules established by Boehm for coefficients and exponents. Comment out if unconstrained drivers are desired.

```
 for(i = 0; i < size; i++) {
  /* get product of cost drivers -- goes from 0 to 89.. treat as a 6x15 array*/
  emm = x[table[i].i1];
  emm *= x[table[i].i2 + 6];
  emm *= x[table[i].i3 + 6*2];
  emm *= x[table[i].i4 + 6*3];
  emm *= x[table[i].i5 + 6*4];
  emm *= x[table[i].i6 + 6*5];
  emm *= x[table[i].i7 + 6*6];
  emm *= x[table[i].i8 + 6*7];
  emm *= x[table[i].i9 + 6*8];
  emm *= x[table[i].i10 + 6*9];
  emm *= x[table[i].i11 + 6*10];
  emm *= x[table[i].i12 + 6*11];
  emm *= x[table[i].i13 + 6*12];
  emm *= x[table[i].i14 + 6*13];
  emm *= x[table[i].i15 + 6*14];
  emm *= x[table[i].ie+90]; /* coeff */
  emm *= pow(table[i].akdsi, x[table[i].ie+93]); /* exponent */
  res +=
sqrt(((table[i].effort-emm)/(table[i].effort))*((table[i].effort-emm)/(table[i].effort)));
 }
 return res/size;
}

/* GAeval f1 10:200dg96 */
```

Bold type is fitness measure evaluation. Average relative error is shown.

Bold underlined type is GAucsd 1.4 declaration for the chromosome. Translate as 10 bits per number, range -200 to 200, 96 numbers total.

****

Genetic Algorithm Input Data File: COCOMO Training and Testing Version

Format is {MM_Actual, Adjusted KDSI, 15 Cost Drivers, Mode

Literal Driver Values Defined as:

0 = Very Low
1= Low
2 = Nominal
3 = High
4 = Very High
5 = Extra High

Mode Defined as:

0 = Embedded
1 = Semidetached
2 = Organic

"Table.c"

****

```
{2040, 113, 1, 4, 0, 2, 3, 3, 3, 1, 1, 1, 1, 2, 0, 1, 3, 0},
{243, 132, 2, 4, 1, 2, 2, 1, 1, 3, 4, 3, 3, 3, 3, 3, 2, 1},
{240, 45.6, 0, 4, 0, 2, 2, 1, 2, 1, 3, 0, 2, 3, 0, 2, 3, 2},
{33, 16, 1, 1, 2, 2, 2, 1, 2, 2, 2, 3, 3, 3, 0, 2, 2, 2},
{423, 30, 3, 1, 4, 4, 4, 3, 2, 3, 2, 3, 1, 1, 3, 2, 2, 0},
{321, 18.27, 4, 1, 4, 3, 5, 2, 3, 3, 4, 3, 3, 2, 2, 2, 2, 0},
{218, 20.16, 4, 1, 4, 3, 5, 2, 3, 3, 4, 3, 3, 2, 2, 2, 2, 0},
{40, 3.66, 4, 2, 4, 4, 5, 2, 1, 3, 2, 3, 2, 2, 2, 2, 2, 0},
{6400, 287.04, 4, 3, 4, 3, 4, 3, 3, 3, 4, 4, 2, 1, 1, 0, 2, 1, 1},
{2455, 252, 2, 4, 3, 3, 3, 1, 1, 3, 2, 2, 2, 2, 3, 3, 2, 0},
{724, 108.56, 3, 2, 2, 4, 3, 2, 2, 3, 4, 3, 3, 2, 3, 2, 0, 0},
{539, 75.46, 3, 2, 2, 3, 3, 2, 2, 3, 4, 3, 3, 2, 2, 2, 0, 0},
{453, 90, 1, 2, 1, 3, 3, 2, 1, 2, 0, 2, 1, 3, 4, 4, 2, 1},
{523, 38, 3, 4, 4, 3, 3, 2, 1, 3, 2, 3, 1, 2, 4, 3, 1, 0},
{387, 48, 1, 2, 1, 3, 3, 3, 3, 3, 2, 3, 1, 2, 3, 1, 1, 0},
{98, 13, 3, 3, 4, 3, 4, 3, 3, 3, 2, 3, 1, 1, 1, 1, 2, 2},
{1063, 50.22, 4, 3, 2, 4, 5, 3, 3, 3, 4, 3, 1, 1, 2, 2, 2, 0},
{702, 261.3, 1, 3, 1, 2, 2, 2, 2, 4, 4, 2, 2, 2, 1, 1, 2, 1},
{605, 40.32, 4, 3, 4, 4, 5, 3, 1, 3, 4, 3, 3, 2, 3, 3, 2, 0},
```

{230, 22.08, 3, 3, 2, 3, 2, 2, 1, 2, 2, 2, 2, 2, 3, 1, 0, 0},
{82, 13, 0, 1, 4, 3, 4, 3, 2, 2, 3, 2, 1, 2, 0, 0, 2, 0},
{55, 12.15, 1, 3, 1, 2, 2, 1, 1, 1, 2, 1, 3, 3, 2, 3, 3, 1},
{8, 2.49, 2, 1, 4, 2, 2, 2, 1, 3, 4, 1, 2, 2, 1, 2, 2, 2},
{6, 5.3, 1, 1, 2, 2, 2, 1, 1, 2, 4, 4, 3, 3, 3, 3, 2, 2},
{45, 19.565, 1, 2, 2, 2, 3, 1, 3, 3, 2, 3, 3, 3, 3, 3, 3, 2},
{83, 28.028, 2, 2, 2, 2, 4, 1, 3, 3, 2, 2, 3, 3, 2, 2, 3, 2},
{87, 29.988, 1, 2, 2, 3, 4, 1, 3, 2, 2, 2, 3, 3, 1, 2, 3, 2},
{106, 31.85, 1, 2, 2, 2, 3, 1, 3, 2, 2, 2, 3, 3, 2, 3, 3, 2},
{126, 56.94, 1, 2, 2, 2, 3, 1, 3, 2, 2, 3, 3, 3, 2, 2, 3, 2},
{36, 23, 0, 1, 4, 2, 2, 1, 1, 4, 4, 4, 1, 1, 1, 2, 3, 2},
{1272, 310.88, 1, 1, 1, 2, 2, 1, 2, 1, 3, 1, 3, 3, 1, 2, 3, 1},
{156, 91, 2, 2, 1, 2, 2, 2, 1, 4, 2, 4, 1, 2, 4, 3, 2, 1},
{176, 24, 3, 2, 2, 4, 4, 2, 1, 3, 2, 3, 1, 2, 2, 2, 2, 0},
{122, 10, 1, 2, 2, 2, 2, 2, 4, 1, 2, 0, 2, 3, 0, 1, 3, 2},
{14, 5.3, 1, 1, 3, 3, 4, 4, 2, 4, 2, 4, 1, 1, 2, 1, 1, 1},
{20, 4.4, 2, 1, 2, 2, 3, 3, 1, 2, 4, 2, 2, 3, 3, 1, 2, 2},
{18, 6.3, 1, 1, 0, 2, 2, 1, 1, 3, 4, 1, 3, 3, 1, 2, 2, 2},
{958, 27, 3, 1, 4, 4, 4, 2, 2, 3, 3, 2, 1, 1, 1, 1, 1, 0},
{237, 14.79, 2, 1, 3, 3, 4, 4, 2, 2, 2, 2, 1, 1, 1, 1, 0, 0},
{130, 25, 4, 1, 4, 5, 4, 2, 2, 4, 4, 4, 3, 3, 3, 2, 2, 0},
{38, 9.1, 1, 1, 4, 3, 4, 3, 2, 4, 4, 4, 0, 0, 3, 0, 2, 1},
{15, 10, 2, 1, 3, 2, 2, 2, 1, 4, 4, 3, 2, 2, 4, 2, 2, 0},

APPENDIX G

****

Genetic Programming Fitness Function File

"fitness.c"

****

```
#include <math.h>
/*
SGPC: Simple Genetic Programming in C
(c) 1993 by Walter Alden Tackett and Aviram Carmi

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- The authors are not responsible for the consequences of use of this
  software, no matter how awful, even if they arise from flaws in it.

If you make changes to the code, or have suggestions for changes,
let us know!  (gpc@ipld01.hac.com)
*/
#ifndef lint
```

```
static char fitness_c_rcsid[]="$Id: fitness.c,v 2.8 1993/04/14 05:19:57 gpc-avc Exp
gpc-avc $";
#endif
/*
 *
 * $Log: fitness.c,v $
 * Revision 2.8  1993/04/14  05:19:57  gpc-avc
 * just a revision number change
 *
 *
 */
#include <stdio.h>
#include <malloc.h>
#include <errno.h>
#include "gpc.h"
#include EXP
#include VAL_EXP
extern terminal_table_entry terminal_table[];
extern int terminal_table_sz ;
extern int total_vars ;
extern int fitness_table_sz;
/*              */
#ifdef ANSI_FUNC
VOID define_fitness_cases(
 int            numpops,
 int            numgens,
 pop_struct   *pop
   )
#else
VOID define_fitness_cases(numpops,numgens,pop)
 int            numpops;
 int            numgens;
 pop_struct   *pop;
#endif
{
#if 0
 /* this template makes all of the fitness cases the same for all
   populations, but that isn't necessary */
 int p,i;
 float range;
 numfc = 10;   /* number of fitness or training cases */
 numtc = 10;   /* number of test or validation cases */
 range = 1.0;
```

```
  fitness_cases_table = (float **) malloc(numpops*sizeof(float *));
  test_cases_table = (float **) malloc(numpops*sizeof(float *));
  fitness_cases_table_out = (float **) malloc(numpops*sizeof(float *));
  test_cases_table_out = (float **) malloc(numpops*sizeof(float *));
  for (p=0; p<numpops; p++) {
   fitness_cases_table[p] = (float *) malloc(numfc * sizeof(float));
   test_cases_table[p] = (float *) malloc(numtc * sizeof(float));
   fitness_cases_table_out[p] = (float *) malloc(numfc * sizeof(float));
   test_cases_table_out[p] = (float *) malloc(numtc * sizeof(float));
   for (i=0; i<numfc; i++) {
    /*    evenly spaced zero..'range': */
    fitness_cases_table[p][i] = range * (float)i / (float)numfc;
    /*    evenly spaced 'range' about zero:
    fitness_cases_table[p][i] = (2.0*range*(float)i/(float)numfc)-range;
    */
    fitness_cases_table_out[p][i] =
     regression_function(fitness_cases_table[p][i]);
   }
   for (i=0; i<numtc; i++) {
    /* validation test cases same as the training set */
    test_cases_table[p][i] = fitness_cases_table[p][i];
    /* validation could be random within the range:
    test_cases_table[p][i] = random_float(range);
    or range centered about zero:
    test_cases_table[p][i] = random_float(2.0*range)-range;
    */
    test_cases_table_out[p][i] = regression_function(test_cases_table[p][i]);
   }
  }
#endif
  /* no processing needed -- we've got data! */
}
#ifdef ANSI_FUNC
VOID evaluate_fitness_of_populations(
    int         numpops,
    int         numgens,
    pop_struct*pop,
    int         p
    )
#else
VOID evaluate_fitness_of_populations(numpops,numgens,pop,p)
    int         numpops;
    int         numgens;
```

```
    pop_struct *pop;
    int         p;
#endif
{
 int            i;
 for (i=0; i<pop[p].population_size; i++) {
  pop[p].standardized_fitness[i] =
   evaluate_fitness_of_individual(pop,p,pop[p].population[i],i);
 }
}
#ifdef ANSI_FUNC
float evaluate_fitness_of_individual(
    pop_struct *pop,
    int         p,
    tree        *t,
    int         i
    )
#else
float evaluate_fitness_of_individual(pop, p, t, i)
    pop_struct *pop;
    int         p;
    tree        *t;
    int         i;
#endif
{
 int            j;
 float                  res,sum = 0.0;
 for (j=0; j<fitness_table_sz; j++) {
  load_terminal_set_values(pop,p,&(fitness_table_t[j][1]));
  sum += (float)sqrt((double)(fitness_table_t[j][0]-eval(t))*
    (fitness_table_t[j][0]-eval(t)) / fitness_table_t[j][0] / fitness_table_t[j][0]);
 }
 res = sum/((GENERIC)fitness_table_sz);
 if(!all_vars(pop,p,t)) {
    res *= 100;
 }
 return res;
}
#ifdef ANSI_FUNC
float validate_fitness_of_tree(
    int         numpops,
    int         numgens,
    pop_struct *pop,
```

Bold type defines the fitness measure of testing data set. Average relative error is shown

```
    int         p,
    tree        *t
    )
#else
float validate_fitness_of_tree(numpops, numgens, pop, p, t)
  int           numpops;
  int           numgens;
  pop_struct    *pop;
  int           p;
  tree                  *t;
#endif
{
  int           j;
  float                 res, sum = 0.0;
  float       ev;
  extern int val_fitness_table_sz;
  for (j=0; j<val_fitness_table_sz; j++) {
    load_terminal_set_values(pop,p,&(val_fitness_table_t[j][1]));
    ev = eval(t);
    sum += (float)sqrt((double)(val_fitness_table_t[j][0]-ev)*
      (val_fitness_table_t[j][0]-ev) / val_fitness_table_t[j][0] /
val_fitness_table_t[j][0]);
  }
  res = sum/((GENERIC)val_fitness_table_sz);
  if(!all_vars(pop,p,t)) {
      res *= 100;
  }
  return res;

}

#ifdef ANSI_FUNC
int terminate_early(
  int           numpops,
  int           numgens,
  pop_struct    *pop
  )
#else
int terminate_early(numpops,numgens,pop)
  int           numpops;
  int           numgens;
  pop_struct    *pop;
#endif
```

Bold type defines the fitness measure of testing data set. Average relative error is shown.

```
{
 int p,i;
 for (p=0; p<numpops; p++) {
  for (i=0; i<pop[p].population_size; i++) {
   if (pop[p].standardized_fitness[i] <= 0.0) {
    return 1;
   }
  }
 }
 return 0;
}
```

****

Genetic Programming Training Data Input File

COCOMO Training and Testing Version

"cotr42.c"

****

```
#include <stdio.h>
#include "gpc.h"
#include "prob.h"
#include "cotr42.h"

GENERIC random_constant();
terminal_table_entry terminal_table[] = {
    {0, "X0",random_constant},
    {1, "X1",random_constant},
    {2, "X2",random_constant},
    {3, "X3",random_constant},
    {4, "X4",random_constant},
    {5, "X5",random_constant},
    {6, "X6",random_constant},
    {7, "X7",random_constant},
    {8, "X8",random_constant},
    {9, "X9",random_constant},
    {10, "X10",random_constant},
    {11, "X11",random_constant},
    {12, "X12",random_constant},
    {13, "X13",random_constant},
    {14, "X14",random_constant},
    {15, "X15",random_constant},
```

X0 = KDSI

X1 = AAF

X2 through X16 are the cost driver values, RELY through SCED.

```
    {16, "X16",random_constant},
    {0,FORMAT,random_constant},
};

int terminal_table_sz = sizeof(terminal_table)/sizeof(terminal_table_entry) - 1;
int total_vars = FITNESS_HEIGHT;
GENERIC fitness_table_t[FITNESS_WIDTH][FITNESS_HEIGHT] = {  {2040.0000,
113.0000,      1.0000,      0.8800,      1.1600,      0.7000,      1.0000,
 1.0600,      1.1500,      1.0700,      1.1900,      1.1300,      1.1700,
 1.1000,      1.0000,      1.2400,      1.1000,      1.0400,      },
    {243.0000,      132.0000,      1.0000,      1.0000,      1.1600,
0.8500,      1.0000,      1.0000,      0.8700,      0.9400,      0.8600,
 0.8200,      0.8600,      0.9000,      0.9500,      0.9100,      0.9100,
 1.0000,      },
    {240.0000,      60.0000,      0.7600,      0.7500,      1.1600,
0.7000,      1.0000,      1.0000,      0.8700,      1.0000,      1.1900,
 0.9100,      1.4200,      1.0000,      0.9500,      1.2400,      1.0000,
 1.0400,      },
    { 33.0000,      16.0000,      1.0000,      0.8800,      0.9400,
1.0000,      1.0000,      1.0000,      0.8700,      1.0000,      1.0000,
 1.0000,      0.8600,      0.9000,      0.9500,      1.2400,      1.0000,
 1.0000,      },
    {423.0000,      30.0000,      1.0000,      1.1500,      0.9400,
1.3000,      1.3000,      1.2100,      1.1500,      1.0000,      0.8600,
 1.0000,      0.8600,      1.1000,      1.0700,      0.9100,      1.0000,
 1.0000,      },
    {321.0000,      29.0000,      0.6300,      1.4000,      0.9400,
1.3000,      1.1100,      1.5600,      1.0000,      1.0700,      0.8600,
 0.8200,      0.8600,      0.9000,      1.0000,      1.0000,      1.0000,
 1.0000,      },
    {218.0000,      32.0000,      0.6300,      1.4000,      0.9400,
1.3000,      1.1100,      1.5600,      1.0000,      1.0700,      0.8600,
 0.8200,      0.8600,      0.9000,      1.0000,      1.0000,      1.0000,
 1.0000,      },
    { 40.0000,      6.1000,      0.6000,      1.4000,      1.0000,
1.3000,      1.3000,      1.5600,      1.0000,      0.8700,      0.8600,
 1.0000,      0.8600,      1.0000,      1.0000,      1.0000,      1.0000,
 1.0000,      },
    {6400.0000,      299.0000,      0.9600,      1.4000,      1.0800,
1.3000,      1.1100,      1.2100,      1.1500,      1.0700,      0.7100,
 0.8200,      1.0800,      1.1000,      1.0700,      1.2400,      1.0000,
 1.0800,      },
```

{2455.0000, 252.0000, 1.0000, 1.0000, 1.1600,
1.1500, 1.0600, 1.1400, 0.8700, 0.8700, 0.8600,
1.0000, 1.0000, 1.0000, 1.0000, 0.9100, 0.9100,
1.0000, },
{724.0000, 118.0000, 0.9200, 1.1500, 1.0000,
1.0000, 1.2700, 1.0600, 1.0000, 1.0000, 0.8600,
0.8200, 0.8600, 0.9000, 1.0000, 0.9100, 1.0000,
1.2300, },
{539.0000, 77.0000, 0.9800, 1.1500, 1.0000,
1.0000, 1.0800, 1.0600, 1.0000, 1.0000, 0.8600,
0.8200, 0.8600, 0.9000, 1.0000, 1.0000, 1.0000,
1.2300, },
{453.0000, 90.0000, 1.0000, 0.8800, 1.0000,
0.8500, 1.0600, 1.0600, 1.0000, 0.8700, 1.0000,
1.2900, 1.0000, 1.1000, 0.9500, 0.8200, 0.8300,
1.0000, },
{523.0000, 38.0000, 1.0000, 1.1500, 1.1600,
1.3000, 1.1500, 1.0600, 1.0000, 0.8700, 0.8600,
1.0000, 0.8600, 1.1000, 1.0000, 0.8200, 0.9100,
1.0800, },
{387.0000, 48.0000, 1.0000, 0.9400, 1.0000,
0.8500, 1.0700, 1.0600, 1.1500, 1.0700, 0.8600,
1.0000, 0.8600, 1.1000, 1.0000, 0.9100, 1.1000,
1.0800, },
{ 98.0000, 13.0000, 1.0000, 1.1500, 1.0800,
1.3000, 1.1100, 1.2100, 1.1500, 1.0700, 0.8600,
1.0000, 0.8600, 1.1000, 1.0700, 1.1000, 1.1000,
1.0000, },
{1063.0000, 62.0000, 0.8100, 1.4000, 1.0800,
1.0000, 1.4800, 1.5600, 1.1500, 1.0700, 0.8600,
0.8200, 0.8600, 1.1000, 1.0700, 1.0000, 1.0000,
1.0000, },
{702.0000, 390.0000, 0.6700, 0.8800, 1.0800,
0.8500, 1.0000, 1.0000, 1.0000, 1.0000, 0.7100,
0.8200, 1.0000, 1.0000, 1.0000, 1.1000, 1.1000,
1.0000, },
{605.0000, 42.0000, 0.9600, 1.4000, 1.0800,
1.3000, 1.4800, 1.5600, 1.1500, 0.9400, 0.8600,
0.8200, 0.8600, 0.9000, 1.0000, 0.9100, 0.9100,
1.0000, },
{230.0000, 23.0000, 0.9600, 1.1500, 1.0800,
1.0000, 1.0600, 1.0000, 1.0000, 0.8700, 1.0000,

```
 1.0000,     1.0000,     1.0000,     1.0000,     0.9100,     1.1000,
 1.2300,     },
    { 82.0000,     13.0000,     1.0000,     0.7500,     0.9400,
1.3000,     1.0600,     1.2100,     1.1500,     1.0000,     1.0000,
 0.9100,     1.0000,     1.1000,     1.0000,     1.2400,     1.2400,
 1.0000,     },
    { 55.0000,     15.0000,     0.8100,     0.8800,     1.0800,
0.8500,     1.0000,     1.0000,     0.8700,     0.8700,     1.1900,
 1.0000,     1.1700,     0.9000,     0.9500,     1.0000,     0.9100,
 1.0400,     },
    { 8.0000,     3.0000,     0.8300,     1.0000,     0.9400,
1.3000,     1.0000,     1.0000,     1.0000,     0.8700,     0.8600,
 0.8200,     1.1700,     1.0000,     1.0000,     1.1000,     1.0000,
 1.0000,     },
    { 6.0000,     5.3000,     1.0000,     0.8800,     0.9400,
1.0000,     1.0000,     1.0000,     0.8700,     0.8700,     1.0000,
 0.8200,     0.7000,     0.9000,     0.9500,     0.9100,     0.9100,
 1.0000,     },
    { 45.0000,     45.5000,     0.4300,     0.8800,     1.0400,
1.0700,     1.0000,     1.0600,     0.8700,     1.0700,     0.8600,
 1.0000,     0.9300,     0.9000,     0.9500,     0.9500,     0.9500,
 1.0400,     },
    { 83.0000,     28.6000,     0.9800,     1.0000,     1.0400,
1.0700,     1.0000,     1.2100,     0.8700,     1.0700,     0.8600,
 1.0000,     1.0000,     0.9000,     0.9500,     1.0000,     1.0000,
 1.0400,     },
    { 87.0000,     30.6000,     0.9800,     0.8800,     1.0400,
1.0700,     1.0600,     1.2100,     0.8700,     1.0700,     1.0000,
 1.0000,     1.0000,     0.9000,     0.9500,     1.1000,     1.0000,
 1.0400,     },
    {106.0000,     35.0000,     0.9100,     0.8800,     1.0400,
1.0700,     1.0000,     1.0600,     0.8700,     1.0700,     1.0000,
 1.0000,     1.0000,     0.9000,     0.9500,     1.0000,     0.9500,
 1.0400,     },
    {126.0000,     73.0000,     0.7800,     0.8800,     1.0400,
1.0700,     1.0000,     1.0600,     0.8700,     1.0700,     1.0000,
 1.0000,     0.8600,     0.9000,     0.9500,     1.0000,     1.0000,
 1.0400,     },
    { 36.0000,     23.0000,     1.0000,     0.7500,     0.9400,
1.3000,     1.0000,     1.0000,     0.8700,     0.8700,     0.7100,
 0.8200,     0.7000,     1.1000,     1.0700,     1.1000,     1.0000,
 1.0400,     },
```

{1272.0000, 464.0000, 0.6700, 0.8800, 0.9400,
0.8500, 1.0000, 1.0000, 0.8700, 1.0000, 1.1900,
0.9100, 1.1700, 0.9000, 0.9500, 1.1000, 1.0000,
1.0400, },
{156.0000, 91.0000, 1.0000, 1.0000, 1.0000,
0.8500, 1.0000, 1.0000, 1.0000, 0.8700, 0.7100,
1.0000, 0.7000, 1.1000, 1.0000, 0.8200, 0.9100,
1.0000, },
{176.0000, 24.0000, 1.0000, 1.1500, 1.0000,
1.0000, 1.3000, 1.2100, 1.0000, 0.8700, 0.8600,
1.0000, 0.8600, 1.1000, 1.0000, 1.0000, 1.0000,
1.0000, },
{122.0000, 10.0000, 1.0000, 0.8800, 1.0000,
1.0000, 1.0000, 1.0000, 1.0000, 1.1500, 1.1900,
1.0000, 1.4200, 1.0000, 0.9500, 1.2400, 1.1000,
1.0400, },
{ 14.0000, 5.3000, 1.0000, 0.8800, 0.9400,
1.1500, 1.1100, 1.2100, 1.3000, 1.0000, 0.7100,
1.0000, 0.7000, 1.1000, 1.0700, 1.0000, 1.1000,
1.0800, },
{ 20.0000, 4.4000, 1.0000, 1.0000, 0.9400,
1.0000, 1.0000, 1.0600, 1.1500, 0.8700, 1.0000,
0.8200, 1.0000, 1.0000, 0.9500, 0.9100, 1.1000,
1.0000, },
{ 18.0000, 6.3000, 1.0000, 0.8800, 0.9400,
0.7000, 1.0000, 1.0000, 0.8700, 0.8700, 0.8600,
0.8200, 1.1700, 0.9000, 0.9500, 1.1000, 1.0000,
1.0000, },
{958.0000, 27.0000, 1.0000, 1.1500, 0.9400,
1.3000, 1.3000, 1.2100, 1.0000, 1.0000, 0.8600,
0.9100, 1.0000, 1.1000, 1.0700, 1.1000, 1.1000,
1.0800, },
{237.0000, 17.0000, 0.8700, 1.0000, 0.9400,
1.1500, 1.1100, 1.2100, 1.3000, 1.0000, 1.0000,
1.0000, 1.0000, 1.1000, 1.0700, 1.1000, 1.1000,
1.2300, },
{130.0000, 25.0000, 1.0000, 1.4000, 0.9400,
1.3000, 1.6600, 1.2100, 1.0000, 1.0000, 0.7100,
0.8200, 0.7000, 0.9000, 0.9500, 0.9100, 1.0000,
1.0000, },
{ 38.0000, 9.1000, 1.0000, 0.8800, 0.9400,
1.3000, 1.1100, 1.2100, 1.1500, 1.0000, 0.7800,

```
 0.8200,      0.7000,      1.2100,      1.1400,      0.9100,      1.2400,
 1.0000,     },
    { 15.0000,      10.0000,      1.0000,      1.0000,      0.9400,
1.1500,      1.0000,      1.0000,      1.0000,      0.8700,      0.7100,
 0.8200,      0.8600,      1.0000,      1.0000,      0.8200,      1.0000,
 1.0000,     },
};
int fitness_table_sz = FITNESS_WIDTH;
GENERIC fitness_table[FITNESS_HEIGHT][FITNESS_WIDTH];
```

****

Perl Script for Creating Genetic Programming Input Training Data File

"define.pl"

(Author: Ranjan Bagchi)

****

```
#!/public/gnu/bin/perl --

# define -- generates static data instantiating all necessary
#         terminals.

$first = 0;
$outf = $ARGV[0];
open(OUT,">$outf.c");
open(OUT_h,">$outf.h");
while(<>) {
  if(/^\w*$/) {
    next;
  }
  @l = split(' ');
  if($first == 0) {
    print OUT
      "#include <stdio.h>\n",
      "#include \"gpc.h\"\n",
      "#include \"prob.h\"\n",
      sprintf("#include \"%s.h\"\n",$outf),
      "\nGENERIC random_constant();\n"
            ;

    print OUT
      "terminal_table_entry terminal_table[] = {\n";
    for(0..$#l-1) {
```

```
        printf(OUT "\t{%d, \"X%d\",random_constant},\n",$_,$_);
    }
    print OUT "\t{0,FORMAT,random_constant},\n";
    print OUT "};\n\
int terminal_table_sz = sizeof(terminal_table)/sizeof(terminal_table_entry) - 1;\n";

    printf (OUT "int total_vars = FITNESS_HEIGHT;\n");
    printf (OUT "GENERIC fitness_table_t[FITNESS_WIDTH][FITNESS_HEIGHT] =
{");
    $format = "\t{"."%8.4f,\t"x($#l+1)."},\n";
  }
  $first ++;
  printf(OUT $format,@l);

}

printf(OUT "};\n");
print OUT "int fitness_table_sz = FITNESS_WIDTH;\n";
print OUT "GENERIC fitness_table[FITNESS_HEIGHT][FITNESS_WIDTH];";
close(OUT);

printf(OUT_h "#define FITNESS_HEIGHT %d\n", $#l+1);
printf(OUT_h "#define FITNESS_WIDTH %d\n", $first);
printf(OUT_h "\n\nextern GENERIC
fitness_table[FITNESS_HEIGHT][FITNESS_WIDTH];\n");
printf(OUT_h "\n\nextern GENERIC
fitness_table_t[FITNESS_WIDTH][FITNESS_HEIGHT];\n");

close (OUT_h);
```

****

Genetic Programming Input Testing Data File

COCOMO Training and Testing Version

"cote21.c"

****

```
#include <stdio.h>
#include "gpc.h"
#include "prob.h"
#include "val_cote21.h"
```

```
GENERIC val_fitness_table_t[VAL_FITNESS_WIDTH][VAL_FITNESS_HEIGHT] = {
{1600.0000,  293.0000,    0.8500,    0.8800,    1.1600,    0.8500,
 1.0000,    1.0600,    1.0000,    1.0700,    1.0000,    0.9100,
 1.0000,    0.9000,    0.9500,    1.1000,    1.0000,    1.0000,
},
      { 43.0000,    4.0000,    1.0000,    0.7500,    1.0000,
0.8500,    1.0000,    1.2100,    1.0000,    1.0000,    1.4600,
 1.0000,    1.4200,    0.9000,    0.9500,    1.2400,    1.1000,
 1.0000,    },
      { 8.0000,    6.9000,    1.0000,    0.7500,    1.0000,
1.0000,    1.0000,    1.0000,    0.8700,    0.8700,    1.0000,
 1.0000,    1.0000,    0.9000,    0.9500,    0.9100,    0.9100,
 1.0000,    },
      {1075.0000,  22.0000,    1.0000,    1.1500,    0.9400,
1.3000,    1.6600,    1.5600,    1.3000,    1.0000,    0.7100,
 0.9100,    1.0000,    1.2100,    1.1400,    1.1000,    1.1000,
 1.0800,    },
      {201.0000,  37.0000,    1.0000,    1.1500,    0.9400,
1.3000,    1.1100,    1.0600,    1.0000,    1.0000,    0.8600,
 0.8200,    0.8600,    1.0000,    0.9500,    0.9100,    1.0000,
 1.0800,    },
      { 79.0000,  25.0000,    0.9600,    1.1500,    0.9400,
1.3000,    1.1100,    1.0600,    1.1500,    1.0000,    0.7100,
 1.0000,    0.7000,    1.1000,    1.0000,    0.8200,    1.0000,
 1.0000,    },
      { 73.0000,  3.0000,    1.0000,    1.1500,    0.9400,
1.6500,    1.3000,    1.5600,    1.1500,    1.0000,    0.8600,
 1.0000,    0.7000,    1.1000,    1.0700,    1.1000,    1.2400,
 1.2300,    },
      { 61.0000,  3.9000,    1.0000,    1.4000,    0.9400,
1.3000,    1.3000,    1.0600,    1.1500,    0.8700,    0.8600,
 1.1300,    0.8600,    1.2100,    1.1400,    0.9100,    1.0000,
 1.2300,    },
      { 9.0000,  3.6000,    0.5300,    1.4000,    1.0000,
1.3000,    1.3000,    1.5600,    1.0000,    0.8700,    0.8600,
 0.8200,    0.8600,    1.0000,    1.0000,    1.0000,    1.0000,
 1.0000,    },
      {11400.0000, 320.0000,    1.0000,    1.1500,    1.1600,
1.1500,    1.3000,    1.2100,    1.0000,    1.0700,    0.8600,
 1.0000,    1.0000,    1.0000,    1.0000,    1.2400,    1.1000,
 1.0800,    },
      {6600.0000,  1150.0000,    0.8400,    1.1500,    1.0800,
1.0000,    1.1100,    1.2100,    0.8700,    0.9400,    0.7100,
```

```
 0.9100,      1.0000,      1.0000,      1.0000,      0.9100,      0.9100,
 1.0000,      },
      { 88.0000,      9.4000,      1.0000,      1.1500,      0.9400,
1.1500,      1.3500,      1.2100,      1.0000,      0.8700,      1.0000,
 1.0000,      1.0000,      1.0000,      1.0000,      0.8200,      1.1000,
 1.0800,      },
      {  7.3000,      2.1400,      1.0000,      0.8800,      1.0000,
1.0000,      1.0000,      1.0000,      1.0000,      1.0000,      1.1000,
 1.2900,      0.8600,      1.0000,      1.0000,      0.9100,      0.9100,
 1.2300,      },
      {  5.9000,      1.9800,      1.0000,      0.8800,      1.0000,
1.0000,      1.0000,      1.0000,      1.0000,      1.0000,      1.0000,
 1.2900,      0.8600,      1.0000,      1.0000,      0.9100,      0.9100,
 1.2300,      },
      { 47.0000,      60.0000,      0.5600,      0.8800,      0.9400,
0.7000,      1.0000,      1.0600,      1.0000,      1.0000,      0.8600,
 0.8200,      0.8600,      1.0000,      1.0000,      1.0000,      1.0000,
 1.0000,      },
      { 12.0000,      15.0000,      1.0000,      1.0000,      1.0000,
1.1500,      1.0000,      1.0000,      0.8700,      0.8700,      0.7100,
 0.9100,      1.0000,      0.9000,      0.9500,      0.8200,      0.9100,
 1.0000,      },
      {  8.0000,      6.2000,      1.0000,      1.0000,      1.0000,
1.1500,      1.0000,      1.0000,      0.8700,      1.0000,      0.7100,
 0.8200,      0.7000,      1.0000,      0.9500,      0.9100,      1.1000,
 1.0000,      },
      { 41.0000,      8.2000,      1.0000,      0.8800,      0.9400,
0.8500,      1.0000,      1.0600,      1.1500,      1.0000,      1.0000,
 1.0000,      1.0000,      1.1000,      1.0700,      1.2400,      1.1000,
 1.0000,      },
      { 70.0000,      23.0000,      0.9000,      1.0000,      0.9400,
1.1500,      1.0600,      1.0600,      1.0000,      0.8700,      1.0000,
 1.0000,      1.0000,      1.0000,      1.0000,      0.9100,      1.0000,
 1.0000,      },
      { 57.0000,      6.7000,      1.0000,      1.1500,      0.9400,
1.3000,      1.1100,      1.0600,      1.0000,      1.0000,      0.8600,
 1.1300,      0.8600,      1.1000,      1.0700,      1.1000,      1.1000,
 1.0800,      },
      { 50.0000,      28.0000,      1.0000,      1.0000,      0.9400,
1.1500,      1.0000,      1.0000,      0.8700,      0.8700,      0.8600,
 1.0000,      0.8600,      0.9000,      1.0000,      0.8200,      1.0000,
 1.0000,      },
};
```

```
int val_fitness_table_sz = VAL_FITNESS_WIDTH;
GENERIC val_fitness_table[VAL_FITNESS_HEIGHT][VAL_FITNESS_WIDTH];
```

****

Perl Script for Creating Genetic Programming Input Testing Data File

"val_define.pl"
(Author: Ranjan Bagchi)

****

```
#!/public/gnu/bin/perl --

# define -- generates static data instantiating all necessary
#         terminals.

$first = 0;
$outf = "val_$ARGV[0]";
open(OUT,">$outf.c");
open(OUT_h,">$outf.h");
while(<>) {
   if(/^\w*$/) {
        next;
   }
   @l = split(' ');
   if($first == 0) {
        print OUT
           "#include <stdio.h>\n",
           "#include \"gpc.h\"\n",
           "#include \"prob.h\"\n",
           sprintf("#include \"%s.h\"\n",$outf),
           "GENERIC
val_fitness_table_t[VAL_FITNESS_WIDTH][VAL_FITNESS_HEIGHT] = {";

        $format = "\t{"."%8.4f,\t"x($#l+1)."},\n";
   }
   $first ++;
   printf(OUT $format,@l);

}

printf(OUT "};\n");
print OUT "int val_fitness_table_sz = VAL_FITNESS_WIDTH;\n";
print OUT "GENERIC
val_fitness_table[VAL_FITNESS_HEIGHT][VAL_FITNESS_WIDTH];";
```

```
close(OUT);

printf(OUT_h "#define VAL_FITNESS_HEIGHT %d\n", $#l+1);
printf(OUT_h "#define VAL_FITNESS_WIDTH %d\n", $first);
printf(OUT_h "\n\nextern GENERIC
val_fitness_table[VAL_FITNESS_HEIGHT][VAL_FITNESS_WIDTH];\n");
printf(OUT_h "\n\nextern GENERIC
val_fitness_table_t[VAL_FITNESS_WIDTH][VAL_FITNESS_HEIGHT];\n");

close (OUT_h);
```

****

SGPC Makefile

COCOMO Training and Testing Phase

****

```
##
## SGPC: Simple Genetic Programming in C
## (c) 1993 by Walter Alden Tackett and Aviram Carmi
##
##  This code and documentation is copyrighted and is not in the public domain.
##  All rights reserved.
##
## - This notice may not be removed or altered.
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## - You may not try to make money by distributing the package or by using the
##   process that the code creates.
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##   changes and notifying the principal author.
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##   misrepresented as being the original software.  Since few users ever read
##   sources, credits must appear in the documentation.
##
## - The authors are not responsible for the consequences of use of this
##   software, no matter how awful, even if they arise from flaws in it.
```

```
##
## If you make changes to the code, or have suggestions for changes,
## let us know!  (gpc@ipld01.hac.com)


# $Id: Makefile,v 1.1 1993/04/30 05:01:48 gpc-avc Exp gpc-avc $
#
# invoke this Makefile with the command:  make [ TYPE=type ]
#
# where you have the problem-specific fitness and setup files named
# fitness.c and setup.c
#
# TYPE should usually equal int or float,  but in principle can be anything.
#
# $Log: Makefile,v $
# Revision 1.1  1993/04/30  05:01:48  gpc-avc
# Initial revision
#
# Revision 1.7  1993/04/23  01:56:25  gpc-avc
#


TYPE = float
DEBUG = 0
EXP = cotr42
VAL_EXP = val_cote21
FLAGS = -O -DTYPE=$(TYPE) -DDEBUG=$(DEBUG)
-DVAL_EXP=\"$(VAL_EXP).h\" -DEXP=\"$(EXP).h\"


SRCS = setup.c fitness.c $(EXP).c main.c  $(VAL_EXP).c
INCS = prob.h
OBJS = $(SRCS:%.c=%.o)
EXE  = gpc-1$(PROBLEM)

## NOTE: last definition wins ##
CC = gcc

CFLAGS =   -g -I../lib
#CFLAGS = -O -I../lib

CPPFLAGS = $(FLAGS)
LIBS = -L../lib -lgpc$(TYPE) -lm
```

Bold type indicates problem specific declarations that include the COCOMO training and testing files created by define.pl and val_define.pl

```
gcc cc debug-cc debug-gcc purify prof all: $(OBJS)
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
        CC=$(CC) CFLAGS="$(CFLAGS)" $@)
        $(CC) -o $(EXE) $(OBJS) $(LIBS)

clean:
        /bin/rm -f $(EXE) $(OBJS) Makefile.bak

real-clean: clean
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
        CC=$(CC) CFLAGS="$(CFLAGS)" clean)

print:
        lwf -s7 -l -p"-2 -t" -m -t8 $(SRCS) $(INCS) | lpr
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
        CC=$(CC) CFLAGS="$(CFLAGS)" $@)

co:
        -co -l $(SRCS) $(INCS) Makefile
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
        CC=$(CC) CFLAGS="$(CFLAGS)" $@)

ci:
        -ci -l $(SRCS) $(INCS) Makefile
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
        CC=$(CC) CFLAGS="$(CFLAGS)" $@)

lint :
        $(LINT.c) $(CFLAGS) $(FLAGS) $(SRCS)
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
        CC=$(CC) CFLAGS="$(CFLAGS)" $@)

depend:
        makedepend -- $(CFLAGS) -- $(FLAGS) $(SRCS)
        ( cd ../lib; \
        $(MAKE) TYPE=$(TYPE) DEBUG=$(DEBUG) \
```

```
	CC=$(CC) CFLAGS="$(CFLAGS)" $@)

# DO NOT DELETE THIS LINE -- make depend depends on it.

setup.o: /usr/include/stdio.h ../lib/gpc.h ../lib/proto.h ../lib/random.h
setup.o: prob.h
fitness.o: /usr/include/stdio.h /usr/include/malloc.h /usr/include/errno.h
fitness.o: /usr/include/sys/errno.h ../lib/gpc.h ../lib/proto.h
fitness.o: ../lib/random.h
```

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